Do Kidney Exchanges Improve Patient Outcomes? An Analysis of Crowd-Out, Graft Survival, and Match Quality

Keith F. Teltser*†

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Abstract

Addressing the increasingly unmet demand for transplantable kidneys in the U.S. requires creativity due to legislation that prohibits buying and selling organs. In order to increase the number of successful transplants that take place, economists, computer scientists, and transplant professionals have begun collaborating to implement kidney exchange programs where patients can "swap" their willing but incompatible living donors. In this paper, I first estimate the number of additional transplants generated by kidney exchanges by analyzing how the probability of receiving an exchange transplant affects the probability that a patient experiences other transplant outcomes, including death while waiting. To do this, I create a novel measure of exchange prevalence that exploits variation in exchange activity across time and transplant centers, as well as the importance of patient proximity to centers performing exchanges. I find that 6.2 of every 10 exchange transplants represent living donor transplants that would not have occurred in the absence of exchange. Using the same approach, I find a small negative but insignificant effect on tissue type match quality. However, I also find that a ten percentage point increase in the probability of receiving an exchange transplant has a small but statistically significant positive effect on graft survival, and reduces waiting time by almost 2 months (10 percent). Back-of-the-envelope calculations based on these findings and prior research suggest that, on average, every 10 exchange transplants reduce health care costs by \$715,000 to \$1.15 million and increase net social welfare by \$2.8 to \$6.8 million.

1 Introduction

In 2014, 4,628 people died waiting for a kidney transplant. In the same year, 36,159 people entered a waiting list for a kidney, and only 17,108 people received a kidney transplant (OPTN, 2016). Figure 1 shows the dramatic growth in the waiting list for kidneys over time, while transplants grow at a much slower pace. Addressing the increasingly unmet demand for transplantable kidneys in the U.S. while maintaining or increasing transplant quality requires creativity due to the National Organ Transplantation Act (NOTA) of 1984, which banned the sale of human organs.

[Insert Figure 1 Here]

As early as the year 2000, transplant centers have been attempting to increase the number and quality of transplants by facilitating kidney exchanges among patients with willing but incompatible living donors. In the most basic type of exchange, a two-way *paired exchange*, patients may "swap" their willing donors when the donor from one pair is a match for the patient in another and vice versa. Paired exchanges can be extended into *donor chains*, where an altruistic donor starts a series of paired exchanges by donating anonymously to a patient with a willing incompatible donor. Another variation is *list exchange*, where a willing donor gives a kidney to someone on the waiting list in exchange for the next compatible deceased donor kidney for his or her intended patient in need (Delmonico et al., 2004).

Roth, Sönmez, Ünver, and other coauthors made large contributions to the development of kidney exchanges by applying existing mechanism design literature to the patient-donor matching problem, simulating and comparing the effectiveness of various mechanisms, and aiding in the real-world implementation of exchange programs (e.g., Roth et al., 2004; Roth et al., 2005b). In addition to kidney exchange, matching techniques have been applied to school choice problems (Abdulkadiroğlu et al., 2005) and medical resident placement (Roth and Peranson, 1999; Niederle and Roth, 2007). However, the case of kidney exchange is unique in that, in addition to reducing frictions through centralized matching, it effectively enables pa-

tients to legally barter with willing living donors' kidneys. Absent kidney exchange, patients in the market for kidney transplants are entirely dependent on centrally-allocated deceased donor kidneys or transplants from known and compatible living donors.

Simulations in Roth et al. (2004) demonstrate the potential of exchange to increase the number of living donor transplants, while also accounting for the possibility that patients will substitute toward exchanges from *direct living* donors - those who give to known and directly compatible patients. If no exchange recipients substitute in this way, then every exchange transplant is a new transplant. If all exchange patients substitute in this way, then exchange programs may not increase transplant quantity at all. The opposing trends in direct living, paired exchanges, and list exchanges observed from 2005 to 2014 in Figures 2, 3, and 4 are consistent with the hypothesis that at least some patients receiving kidneys via paired and list exchange would have received a direct living transplant in the absence of exchange.

Figure 2 shows considerable growth in paired and list exchanges starting around 2005; exchanges increased from 0.6 percent of all living donor transplants in 2005 to 12.5 percent in 2014 (OPTN, 2016). While the downward trend in living donor transplants from 2005 to 2014 seen in Figures 3 and 4 is concerning, Figure 4 highlights that this downtrend would have been even more pronounced in the absence of kidney exchange. Additionally, from 2005 to 2014 we see growth in transplants from *anonymous* donors - those who give to unknown patients. The growth of kidney exchange may explain this observation, since anonymous donations can facilitate more transplants when used to start donor chains. The introduction of exchange may therefore partially crowd out direct living donations due to substitution while also crowding in anonymous donations.

[Insert Figures 2, 3, 4 Here]

Roth et al. (2004) also predict improvements in tissue type compatibility as measured by the number of Human Leukocyte Antigen (HLA) mismatches. However, the authors obtain their results under a set of necessary restrictions and strong assumptions about patient

preferences. Moreover, the simulations cannot account for potential growth in anonymous donations. As a result, the extent to which the introduction of kidney exchange affects the quantity and quality of kidney transplants remains an empirical question.

My paper is the first to analyze the causal relationship between the introduction of exchange and observed patient outcomes. I first estimate the number of additional transplants generated by kidney exchanges by analyzing how the probability of receiving an exchange transplant affects the probability that a patient experiences other transplant outcomes, including death while waiting. I do this using OPTN Standard Transplant and Analysis Research (STAR) files, which contain the universe of waiting list registrations and transplants, along with a novel measure of exchange prevalence based on a patient's residential location and month of registration outcome.

Using the same approach, I then estimate the resulting improvements in graft (transplant) survival, match quality, and waiting time. Holding all else equal, we would expect to see improved overall graft survival if more people receive living donations with the introduction of exchange and living donor kidneys yield longer graft survival than deceased donor kidneys.[1,2] Moreover, those who switch from a direct donor to an exchange may do so for reasons that lead to improved graft survival overall.

Specifically, reductions in HLA mismatches and waiting list registration duration are associated with improved graft survival according to research in the transplantation literature (Opelz, 1997; Meier-Kriesche et al., 2002; Davis and Delmonico, 2005). With the introduction of exchange, we expect reduced frictions when searching for a living donor. Moreover,

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[1]While there appears to be a lack of causal evidence, it is generally accepted in the transplant community that living donor kidney transplants are more successful than those from deceased donors. Calculations based on OPTN individual-level transplant data, as of 12/31/2014, from 1988 to 2008 reveal that 3.2 percent of living donor kidney grafts failed within one year compared to 7.9 percent of deceased donor kidney grafts. Similarly, 16.8 percent of living donor kidney grafts failed within five years compared to 29.6 percent of deceased donor kidney grafts. Note that these failures also include deaths of those with non-functioning grafts within the specified time-frame. Deaths of those with functioning grafts before one year or five years were excluded from the respective calculations.

[2]In their paper providing an overview of living kidney donation practices as of 2005, Davis and Delmonico (2005) suggest that this is partly due to reduced waiting time and time spent on dialysis for living donor kidney recipients compared to deceased donor kidney recipients.

if exchange increases total living donations, we expect reduced excess demand for deceased donor kidneys. Both of these effects could yield reductions in waiting list registration duration for the exchange recipient and others who are waiting. Exchange also allows patients to search for a better match, rather than having to rely on a compatible friend, relative, or the deceased donor kidney waiting list. Improving match quality is an integral part of finding suitable living donors for hard-to-match patients and, as we will see in Section 3, recipients of kidney exchange tend to be individuals who are harder to match.

The paper proceeds as follows. The remainder of Section 1 provides additional information on kidney transplantation, kidney exchange, and relevant literature. Section 2 presents a conceptual framework modeling the impact of kidney exchange on the decision to donate, which motivates the empirical analysis. Section 3 discusses the data that I use and provides descriptive statistics. I then present an instrumental variable approach to estimating the effect of exchanges on patient outcomes in Section 4, where I use time-varying local kidney exchange activity to predict whether a patient receives a kidney via exchange. Section 5 presents the two-stage least squares (2SLS) estimates, where I find that roughly 6.2 of every 10 transplants via exchange represent living donor transplants that would not have occurred in the absence of exchange. Conditional on receiving a transplant, I find that a ten percentage point increase in the probability of receiving a transplant via exchange increases one-year graft survival by 2 percentage points, two-year graft survival by 1.9 percentage points, and reduces waiting list registration duration by 59.2 days, relative to an average overall one-year graft survival rate of 93 percent, two-year rate of 88 percent, and 597 day registration duration. I find a small negative but insignificant effect of exchange on tissue type match quality. Section 6 briefly discusses the results of various robustness checks. Section 7 presents back-of-the-envelope calculations of the implied cost-savings and welfare gains, and concludes.

1.1   Background on Kidney Transplantation and Kidney Exchange

There are two main treatment options available to a patient experiencing kidney failure: transplantation and dialysis. Dialysis is an ongoing treatment that provides some of the blood filtering that healthy kidneys would perform. However, for those with chronic kidney disease or end-stage renal disease, dialysis is not a cure nor an attractive long-term treatment. These patients can turn to transplantation for a more permanent and flexible solution. Once a patient decides to pursue a kidney transplant, they may register on a waiting list for a deceased donor kidney and/or search for a willing living donor (NKF, 2015).

Looking at Figure 3, deceased donations are by far the most common source of kidney transplants. In 2014 nearly 68 percent, or 11,570 of 17,108, of kidney transplants came from deceased donors (OPTN, 2016) Doctors recover kidneys from eligible deceased donors, which are then allocated by organ procurement organizations (OPOs) across the United States.[3] When a healthy kidney is recovered and becomes available for transplantation, the OPO servicing the area in which the kidney was recovered generates a priority list of compatible patients on the waiting list. This subset of patients is ranked based on factors including tissue match, blood type, length of time on the waiting list, immune status, and distance between the potential recipient and the donor. After the list is generated, the OPO offers the kidney to the transplant team of the first patient (UNOS, 2015).

Blood type compatibility is the first condition that needs to be met for transplant success. In general, people with type O blood can only receive from type O donors, but they can give to any other blood type. People with type A blood can only give to type A or AB patients. People with type B blood can only give to type B or AB patients. Finally, people with type AB blood can only give to type AB patients.

Additional compatibility concerns include tissue type matching and patient sensitivity.

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[3]OPOs, along with all other professionals involved with organ transplantation and donation such as transplant centers and doctors, make up the Organ Procurement and Transplantation Network (OPTN), which is administered by the United Network for Organ Sharing (UNOS). UNOS is a private non-profit organization under contract with the U.S. Department of Health and Human Services (DHHS) to maintain the national organ transplant system.

Tissue type match is based on the number of HLA mismatches between patient and donor, of which there can be between 0 and 6. The more HLA mismatches between the patient and a prospective donor, the more likely it is that the patient's body will reject the transplant in spite of any reasonable immunosuppressive drug treatment. Patient sensitivity is measured by the level of antibodies present in the patient's blood, called the Panel Reactive Antibodies (PRA) score, which takes on a value between 0 to 100 and indicates the percentage of the general population with whom the patient is likely incompatible.

As an alternative to waiting for a deceased donor kidney, patients can search for living donors within their network of family and friends. They may be particularly likely to do so if they feel they face too long of a wait and/or they want to maximize expected graft survival time. Once a patient finds potential donors, they undergo the same compatibility tests that are used for deceased donations. Donors are also screened for heart and lung disease, kidney function, and psychological wellness (UNOS, 2015) An additional constraint facing living donors is the cost of donating. Even though medical expenses for living donation are typically covered by the recipient's insurance or a transplant center's Organ Acquisition Fund, potential donors may not be able to afford the associated travel costs, time off of work, or risk of future medical problems resulting from the procedure (UNOS, 2015).[4]

Most living donations occur because patients find a willing compatible donor. In 2014, nearly 85 percent of living kidney donations were direct living donations (OPTN, 2016). Among direct living donors in 2014, about 15 percent were the patient's spouse or life partner. Roughly 24 percent were the patient's full or half sibling, 16 percent were the patient's child, 10 percent were the patient's parent, 7 percent had some other biological relationship, and 27 percent had some other non-biological relationship to the patient (OPTN, 2016).

Exchange offers an additional living donation option to those who have willing but in-

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[4]Although NOTA explicitly banned the exchange of valuable consideration for organs, it is now legal to reimburse living donors for certain costs incurred including lost wages and travel costs according to Section 3 of the Organ Donation and Recovery Improvement Act (2003). One major source of such reimbursement is the National Living Donor Assistance Center (NLDAC). In addition, certain states have begun implementing tax and paid-time-off incentives for living donors.

compatible donors. Such arrangements include paired exchanges, list exchanges, and donor chains, as discussed in the introduction. In a paired exchange, patients may "swap" their willing donors when the donor from one pair is a match for the patient in another and vice versa. This can be extended to include three or more incompatible pairs as well. Paired exchanges can also take the form of a donor chain, which is not limited to a fixed group of incompatible pairs. To start a donor chain, a non-directed living donor, or "Good Samaritan" donor (according to the National Kidney Registry) who is not giving on behalf of a loved one in need, donates a kidney to a patient who has a willing incompatible donor. The willing donor of the patient receiving the non-directed donor's kidney will then donate to a patient in another incompatible pair. This process continues until no more matches are found, a recipient's willing incompatible donor backs out, or the final willing donor gives to someone on the waiting list who is not part of a pair. Figure 5 depicts diagrams of a two-way exchange, three-way exchange, and donor chain.

[Insert Figure 5 Here]

Exchange arrangements are facilitated by matching incompatible patient-donor pairs who have signed up with an exchange registry. These registries may be managed by a single transplant center, such as the Johns Hopkins University Incompatible Kidney Transplant Program, or by a consortium of transplant centers where centers share their registries, such as the National Kidney Registry and Alliance for Paired Donation. The center or consortium matches pairs in the registry over a range of characteristics similar to those used in ranking candidates for deceased donor kidneys with the objective of maximizing some mix of quantity and quality of matches. Each center or consortium implements its own objective function. For example, the algorithm that the Alliance for Paired Donation uses gives highest priority to patients with high PRA scores, patients who previously donated, patients under 5 years old, and to matches with zero HLA mismatches (APD, 2015).

The first paired exchange in the U.S. occurred in 1994, and the first list exchange in the

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U.S. occurred in 1996 (OPTN, 2016).[5] The "trading" of living donor kidneys via exchange gained traction within the past decade, beginning with the 2003 legal opinion from UNOS that kidney exchanges do not violate NOTA and the passage of HR707 in December of 2007 that changed the law to explicitly allow kidney exchange. In the early years, participating centers found matches manually - looking at medical charts and matching patients to donors by hand (O'Brien and Kellan, 2012; Hanto et al., 2010). In 2005, the New England Paired Kidney Exchange (NEPKE) began using "a computer optimized matching program developed by Roth, Ünver, and Sönmez," where two- and three-way matches were identified "including closed non-directed donor (NDD) and list exchange chains" (Hanto et al., 2010).

[Insert Figure 6 Here]

With computerized matching came sizable gains in transplants via kidney exchange. Figure 2 highlights the growth in popularity of paired and list exchange around this time period (2005-2007). Figure 6 reinforces this, showing rapid growth in the number of transplant centers that performed at least one paired exchange, list exchange, or both in a given year. By 2014, paired exchanges accounted for 9.9 percent of all living kidney transplants and list exchanges accounted for 2.1 percent (OPTN, 2016). The longest reported donor chain to date included 68 people - 34 patients and 34 donors (UW Health, 2015).

1.2 Literature Review

Previous research on organ donation in economics largely focuses on the factors influencing deceased donor kidney supply (Abadie and Gay, 2006; Dickert-Conlin et al., 2011; Kessler and Roth, 2012; Li et al., 2013; Kessler and Roth, 2014; Callison and Levin, 2016), and how changes in the supply of deceased donor kidneys affect living kidney donations (Sweeney, 2010; Fernandez et al., 2013; Dickert-Conlin et al., 2016; Anderson, 2016). In fact, work exploring the latter may help explain part of the observed decline in direct living donations

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[5]The paired exchange in 1994 was an isolated event. None were observed again until 2000.

from 2005 to 2014. For example, Dickert-Conlin et al. (2011) show that the supply of deceased donor kidneys is responsive to changes in motorcycle helmet laws. Follow-up papers by Fernandez et al. (2013) and Dickert-Conlin et al. (2016) show that deceased donor organ supply shocks cause a corresponding decrease in living organ donations. Using alternative identification strategies, Sweeney (2010) and Anderson (2016) also find that increases in the supply of deceased donor organs crowd out living donations.

Related to the idea of exchanging organs, an important body of research in economics focuses on the topic of offering financial incentives for blood and organ donations (e.g., Adams et al., 1999; Byrne and Thompson, 2001; Becker and Elias, 2007; Wellington and Sayre, 2011). Titmuss (1970) famously argued that providing financial incentives for blood donation would undermine efforts to increase the supply of blood by crowding out altruism. This argument has since been used against the notion of allowing payments for organ donation. However, Lacetera et al. (2012a, 2012b) find that financial incentives have a positive impact on blood donations with no detrimental impact on quality. Lacetera et al. (2014) find no effect of state-sponsored tax and paid leave incentives on living kidney donation (though they do find positive effects for bone marrow). However, Schnier et al. (2014) find that transplant center efforts to reimburse donors' travel-related expenses significantly increase living kidney donations.

Until now, research in economics concerning kidney exchange is limited to theoretical work on matching and simulations of patient outcomes (Roth et al., 2004; Roth et al., 2005; Roth et al., 2006; Roth et al., 2007; Ashlagi et al., 2011; Andersson, 2015; Chun et al., 2016). A representative set of simulations from Roth et al. (2004) suggests that one additional transplant via exchange reduces direct living donations by 0.48,[6] which implies

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[6]The researchers simulate fixed pools of 30, 100, and 300 unrelated patient/donor pairs randomly generated to closely reflect OPTN population statistics. They assume that patients' preferences are determined by maximizing the probability of a successful transplant, given certain constraints. The representative simulations cited here use 100 pairs and are based on the assumption that 40% of patients would prefer waiting list priority to their incompatible willing donor's kidney, which allows for the possibility of list exchange. The calculation I use is: $(\frac{Own\ Donor\ TXs\ With\ Exchange - Own\ Donor\ TXs\ Without\ Exchange}{Exchanges})$, where the total number of own donor transplants is 22.81 with exchange and 54.79 without exchange, and the number of exchanges is 66.16. This calculation gives us a crowd-out estimate of $-\frac{31.98}{66.16}$ or -0.48, and yields the following

that 5.2 of every 10 transplants via kidney exchange represent new living donor transplants that would not have occurred in the absence of kidney exchange. The representative set of simulations also yields a post-introduction reduction of average HLA mismatches from 4.83 to 3.85 for those receiving a living donor transplant. These results are based on the assumption that patients are "cautious," meaning that patients will only enter an exchange if their own donor is incompatible or if the match will reduce the number of HLA mismatches by at least one compared to their compatible donor. If instead patients are assumed to be "rational," meaning that they only care about minimizing the number of HLA mismatches and donor age, more patients switch from direct living donors to exchange and the number of additional living donations for every 10 exchanges decreases to 4.4 and the average number of HLA mismatches decreases to 3.71.

However, using the simulated results to estimate substitution and match quality improvement ignores some important considerations. First, the simulations use a fixed set of patient-donor pairs, meaning that they do not allow for possible changes in the number and composition of patient-donor pairs in response to the introduction of exchange. Second, those switching from compatible living donation to exchange in the simulations are driven only by improvements in the number of HLA mismatches and donor age. In reality, many other factors may affect the decision to substitute between these two methods, including concern for donor well-being.

In the transplantation literature, Massie et al. (2013) estimate the potential utilization of kidney exchange (combining paired and list exchange) in the United States if centers achieved several different thresholds of exchange utilization.[7] However, their calculated hypothetical

interpretation: of the 66.16 exchanges performed, 31.98 (or 4.8 out of 10) of the patients involved would have received a living kidney donation otherwise and 66.16 - 31.98 = 34.18 would not. See Table 3 of Roth et al. (2004) for the base numbers.

[7]The authors estimate a set of negative binomial regression of total exchanges, paired and list, on a set of controls for all centers, the top 20 percent in terms of exchange utilization, and the top 10 percent. These controls include center waitlist size, proportion of waitlisted patients that received a directed living donation, distribution of waitlisted patients' race, education, age, insurance, dialysis status, and PRA. They generate the predicted number of exchanges for each transplant center based on the estimated parameters for each utilization level. Then they sum over centers' max(observed exchanges, predicted exchanges) for each utilization level.

gains in exchanges do not necessarily translate into equivalent gains in the number of living donor kidney transplants. As the authors themselves note, "some participants in KPD [kidney paired donation] may have exchanged a kidney from a compatible older donor for a younger donor kidney; others may have eventually located a compatible live donor without KPD, or undergone desensitization." They express the belief "that most KPD recipients would otherwise not have received LDKT [living donor kidney transplant], and that inferences about dissemination of this modality would not be significantly biased by these issues," but do not provide evidence for this claim.

There exists additional descriptive research on survival comparisons between exchange and direct living transplants in the transplantation literature. Segev et al. (2008) find no statistically significant difference in graft survival rates between kidney exchange recipients and direct living recipients, even when controlling for observables. In a review of several exchange programs in the United States, Mierzejewska et al. (2013) report the same findings based on comparisons of mean survival, despite exchange recipients being more sensitized on average. This is consistent with the findings of Delmonico (2004) and Gjertson and Cecka (2000) that the number of HLA mismatches has little to no effect on graft survival of a compatible kidney, but goes against the earlier findings of Opelz (1997). These survival comparisons imply non-negative changes in graft survival for those substituting toward kidney exchange and away from a direct living transplant, and an increase in graft survival for those substituting away from a deceased donor transplant. That said, the comparisons do not provide causal estimates. The limited existing literature on transplant gains and improvements in recipient outcomes invites further research addressing these questions.

2 Conceptual Framework

This section develops the conceptual framework to guide the empirical work of this paper. I ask whether the introduction of exchange increases the number of transplants, and whether patients also experience increased graft survival, increased HLA match quality, and reduced

waiting times. The market for transplantable kidneys is unique in that it revolves around the allocation of life-saving scarce resources without the existence of a formal/legal price mechanism. This market relies on individuals making voluntary contributions upon their death or while they are alive, and living donors often receive little to no financial compensation at all for the costs they incur. Due to the lack of a price mechanism, it is incredibly difficult to analyze the introduction of exchange as one might analyze the introduction of a new product. This is made even more difficult by the fact that patients cannot freely choose from among all of the available options at any given time, and the fact that their choice sets are not observed; the options available to patients depend in large part on the compatibility and decisions of potential donors, as well as the availability of deceased donor kidneys.

The introduction of kidney exchange unlocks a set of potential donors available to a patient in need. A potential living donor must only be willing and eligible to donate; the compatibility of donor and intended recipient is no longer required. The extent to which this pool of potential donors expands is dependent on the benefits and costs involved in giving and receiving a kidney via exchange. These costs and benefits are primarily determined by access to a participating exchange program and the thickness of the market - the number of other accessible incompatible pairs looking to participate in an exchange.

As the pool of potential donors for any given patient expands, the likelihood of finding a suitable living donor changes. This expansion gives patients different choices when seeking out a living donor, which could change patients' utility through the likelihood of receiving a kidney, match quality, utility derived by potential and actual donors, and waiting time. At the same time, as the number of options available to a given patient increases, there is greater incentive for potential donors to free ride. While a patient no longer restricted to finding a compatible living donor or waiting for a deceased donor may find it more beneficial to seek out a transplant via exchange, a potential compatible donor who would have given in the absence of exchange may not be willing to give when compatibility is no longer a strict requirement.

Consider a simple model of the decision to donate for an individual with a loved one in need of a kidney, before and after the introduction of kidney exchange. I will denote this prospective donor with a subscript L, and the patient in need with the subscript k. The prospective donor L derives benefit from patient k's transplant outcome, given by $B_k(Q(Y))$, where B_k is an increasing function of $Q(Y)$. Q represents the expected quality of transplant outcome and is a function of the mode, Y, by which L gives to k. Donor L also faces a cost of donating that may include things such as travel costs, uncovered medical expenses, and time off of work, given by $C(Y)$. Suppose L also cares about the surplus that her transplant generates among other patients in need, $-k$. Finally, suppose donating via exchange is prohibitively costly when exchange has yet to be formally introduced and adopted by transplant centers. Based on this setup, L's general indirect utility is given by the following:

$$U_L(Y) = B_k(Q(Y)) + \alpha_L S_{-k}(Q(Y)) - C(Y) \tag{1}$$

where α_L is a non-negative donor-specific altruism parameter and $S_{-k}(Q(Y))$ represents the total surplus L generates for other patients. Given the size of the kidney shortage and the number of transplants occurring every year, I also make the simplifying assumption that no spillover surplus is generated when L does not donate via exchange, or $S_{-k}(Q^N(Direct)) \approx S_{-k}(Q^N(None)) = 0$.

Before the introduction of exchange, denoted by the superscript N for "no exchange", donor L's expected utility when she donates directly is given by:

$$U_L^N(Direct) = B_k(Q^N(Direct)) - C^N(Direct) \tag{2}$$

When she donates via exchange, her utility is:

$$U_L^N(Exch) = B_k(Q^N(Exch)) + \alpha_L S_{-k}(Q^N(Exch)) - C^N(Exch) \tag{3}$$

When she does not give at all, her reservation utility is:

$$U_L^N(None) = B_k(Q^N(None)) \tag{4}$$

After the introduction of exchange, denoted by the superscript E for "with exchange", donor L's expected utility when she donates directly is given by:

$$U_L^E(Direct) = B_k(Q^E(Direct)) - C^E(Direct) \tag{5}$$

When she gives via exchange, her utility is:

$$U_L^E(Exch) = B_k(Q^E(Exch)) + \alpha_L S_{-k}(Q^E(Exch)) - C^E(Exch) \tag{6}$$

When she does not give at all, her reservation utility is:

$$U_L^E(None) = B_k(Q^E(None)) \tag{7}$$

Since the pool of possible donors available to k expands following the introduction of exchange, prospective donor L should rationally expect that patient k's outcome, when L does not donate, improves following the introduction of exchange (i.e. $Q^E(None) \geq Q^N(None)$). From this starting point, I present the following proposition.

Proposition 1. *If the introduction of exchange does not affect the costs nor the benefits to L of direct donation, i.e. $C^E(Direct) = C^N(Direct)$ and $B_k(Q^E(Direct)) = B_k(Q^N(Direct))$, then L is less likely to choose direct donation over no donation after the introduction of exchange.*

Proof. See Appendix A.1. □

In addition to showing a crowd-out effect of exchange introduction on direct donations, Proposition 1 implies that, after the introduction of exchange, direct donors will be higher

quality matches and/or yield better expected transplant outcomes on average compared to direct donors prior to the introduction of exchange. A direct donor who is marginal, such that $U_L^N(Direct) \geq U_L^N(None)$ and $U_L^E(Direct) < U_L^E(None)$, is only crowded out when her direct donation does not improve k's transplant outcome enough relative to k's expected outcome when she does not donate directly. The marginal direct donors crowded out by the introduction of exchange provide smaller quality improvements on average, relative to their patients' outside options, so therefore we should expect to see direct donation transplant outcomes improve following exchange introduction.

Comparing L's post-introduction utility from donating via exchange compared to directly, note that L is more likely to donate via exchange rather than directly when she is a relatively poor direct match for k. This implies an additional increase in transplant quality for direct donation recipients, as some marginal quality direct donors will substitute toward exchange in order to obtain a higher quality of transplant for their loved one in need. That said, as the cost differential between donating directly compared to via exchange approaches zero, L will choose exchange rather than direct donation if there is any gain in total benefit derived from giving via exchange rather than direct donation. Depending on L's altruism parameter and the amount of expected surplus generated by L's donation via exchange, L may prefer to donate via exchange rather than directly even though it could imply a worse outcome for k.

It is straightforward to show that the probability that L chooses to give via exchange rather than directly or not at all is higher after exchange is introduced, relative to before. This is driven by the assumption that donating via exchange is prohibitively costly when transplant centers have yet to adopt it as a transplant method. The ability to generate surplus for other patients in need through an exchange mechanism provides additional incentive for prospective donors to give via exchange rather than directly or not at all. Note that donors switching from direct donation toward exchange will not change the overall number of living kidney donations. Therefore, to show that exchange will result in a net increase

of living kidney donations, it is sufficient to show that the gain in living donor transplants via exchange will outweigh the loss of living donations due to crowd-out of direct donations.

Proposition 2. *Suppose again that the introduction of exchange does not affect the costs nor the benefits to L of direct donation, i.e. $C^E(Direct) = C^N(Direct)$ and $B_k(Q^E(Direct)) = B_k(Q^N(Direct))$. Then a representative prospective donor L is more likely to become a living kidney donor if the introduction of exchange increases the net utility of donating via exchange, relative to not donating, by a larger magnitude than it increases L's reservation utility, i.e. $[U_L^E(Exch) - U_L^E(None)] - [U_L^N(Exch) - U_L^N(None)] > U_L^E(None) - U_L^N(None)$.*

Proof. See Appendix A.2. □

Given a large enough reduction in the cost of donating via exchange, the condition given in Proposition 2 will hold trivially. But even in the extreme and unrealistic case of zero cost reduction, the condition would hold if the introduction of exchange increases the marginal benefits of donating via exchange, relative to no donation, by a larger magnitude than it increases L's reservation utility. This stronger condition is still relatively weak; L's net expected utility will weakly increase if the formal introduction of exchange substantially increases the thickness of the market, leading to a substantially higher chance of finding a quality match for k and increasing the surplus of other patients $-k$.[8]

The model can be extended to account for increases in anonymous donations as well. Suppose individual A does not have a loved one in need of a kidney but cares about the surplus her donation generates for unknown patients, such that she would get the following utility from donating anonymously in the absence of exchange (again, denoted by superscript N):

$$U_A^N(Anon) = S_i(Q^N(Anon)) - C^N(Anon) \tag{8}$$

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[8]Given a large enough increase in market thickness, net expected utility would remain unchanged only if L is not a suitable exchange donor. In this case, she is also highly unlikely to be a suitable direct donor, so we would expect exchange introduction to have no effect on L's donation decision. Therefore, if L is a suitable exchange donor, then net expected utility would strictly increase with a large enough increase in market thickness.

where S_i is the surplus generated by A's anonymous donation to an unknown patient i. As before, assume that there is no spillover surplus generated in the absence of exchange. In the absence of exchange, her utility is zero when she does not donate:

$$U_A^N(None) = 0 \tag{9}$$

After the introduction of exchange, denoted by the superscript E for "with exchange", donor A's expected utility when she donates anonymously is given by:

$$U_A^E(Anon) = S_i(Q^E(Anon)) + S_{-i}(Q^E(Anon)) - C^E(Anon) \tag{10}$$

Note that the altruism parameter, α, has been dropped as A cares equally about all the potential (unknown, unrelated) beneficiaries. Again, her utility is zero when she does not donate:

$$U_A^E(None) = 0 \tag{11}$$

Proposition 3. *If the cost of donating anonymously is unaffected by the introduction of exchange, i.e. $C^E(Anon) = C^A(Anon)$, then individuals without a loved one in need of a kidney will be more likely to donate anonymously to start a donor chain and less likely to donate anonymously to a single patient following the introduction of exchange.*

Proof. See Appendix A.3. □

Individuals will be less likely to donate anonymously to a single individual compared to not at all for much the same reason as they would be less likely to donate directly. The introduction of exchange reduces the surplus generated by A's donation to i, since it improves i's expected alternative outcome, while the quality of A's transplant for i should not be affected by the existence of exchange. When A donates anonymously in order to start a donor chain, the surplus generated by helping even one additional person receive a transplant via exchange is very likely to at least offset the reduction in surplus experienced by

patient i. Since most donor chains involve more than two patients, the additional surplus is very likely to outweigh the reduction in surplus experienced by i. If all anonymous donations are steered toward donor chains, their donations have the potential to help more patients receive transplants and we would therefore expect that individuals are more likely to donate anonymously after exchange is introduced.

Finally, we should not expect to see any change in deceased donor transplants as long as deceased donation rates do not respond to kidney exchanges. Such a change would require a change in how many people register as donors, the number of families that give consent once a potential donor dies, and/or a change in the number of recovered kidneys deemed transplantable. None of these seem likely given the size of the waiting list and that exchange is still a small share of total transplants despite its recent growth in utilization. Additionally, because the waiting list is so long, there should always be someone willing and able to accept a suitable deceased donor kidney. We may see the allocation of deceased donor organs naturally shift toward areas with fewer paired exchanges, but this should have no effect on the overall number of deceased donor transplants.

3   Data

In the following analysis, I begin with individual-level data extracted on December 31, 2014 from the Standard Transplant Analysis and Research (STAR) file, which is available by request from OPTN. The data contain 788,106 observations of kidney waiting list registrations and transplants that occurred from 1988 to 2014. Of these observations, 398,984 are registrations that resulted in transplants and transplants that occurred without an associated waiting list registration.[9] I have information on the outcome of each registration including: transplant, death, transfer to a different center, or still waiting as of December 31, 2014. I restrict my analysis to observations that resulted in either a transplant or death, as these

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[9]Some recipients of living donor kidneys never register for the deceased donor waiting list. These observations are entered as a transplant record and lack the information that is only relevant when a patient registers on the waiting list.

encompass the clear and well-defined registration outcomes.[10]

"Donor relation" is the key variable I use to determine whether a transplant is a(n) direct living, deceased, anonymous, or exchange transplant. Kidney transplants are coded with one of the following donor relationships: sibling, twin, child, parent, other relative, significant other, miscellaneous unrelated donor, paired exchange, list exchange, anonymous, or deceased.[11] These data are rich; I observe variables including blood type, PRA, race, education, previous transplant status, age, gender, registration date, transplant date, HLA mismatches, additional medical information, donor characteristics, and transplant follow-up information (from which graft survival is calculated). Additionally, through special request I obtained zip code information for patients and transplant centers.

I restrict my analysis to data from January 2000 to July 2014. There is a large increase in the quality of reporting for the donor relationship variable in 2000. From 1988 to 1999, there are an average of 77 unreported donor relationships per year compared to one per year from 2000 to 2013. The data show only one paired exchange and 8 list exchanges occurring before 2000, so there is little reason to be concerned about the exclusion of pre-2000 data. Due to lags in data processing, August through December 2014 are incomplete with respect to donor relationship at the time of my extract.

Table 1 shows the frequency of observed transplant or death outcomes including the following categories: directed living, paired and list exchange, anonymous donation, deceased donation, and death without a transplant. We see that exchanges account for 1.5 percent of observed outcomes, anonymous donations account for 0.5 percent, directed living donations account for 28 percent, deceased donations account for 49 percent, and deaths while waiting account for 21 percent. Comparing the 2013 snapshot, the last complete year of data, to

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[10]Note that patients may have multiple waiting list registrations. Patients with multiple registrations who died while waiting are only counted once, and I use their earliest listing coded as such. For the ending date of these observations, I use the earliest reported registration end date among those coded as removal due to death. For patients who receive a transplant, only one registration will show the transplant outcome, which is the observation I use.

[11]Note: I can only connect donors to their actual recipients. Therefore, with respect to exchanges, I cannot connect donors to the loved one on whose behalf they are donating. Also, I cannot observe whether an anonymous donor's kidney is used to start a donor chain.

the 2007 snapshot, we see that transplants via deceased donation, exchange, and anonymous donation increased in level and percent of outcomes. We also see a decrease in directed living donations and a slight decrease in deaths while waiting.

[Insert Table 1 Here]

Table 2 presents three different measures of mean PRA,[12] patient age at the time of listing, and donor age. Patients who die while waiting for a kidney have the highest PRA scores on average at 23 (C-PRA), followed by exchange at 22, deceased donation at 20, anonymous donation at 17, and recipients of direct living kidneys at a much lower 9. This suggests that those receiving exchanges are ex-ante harder to match. It is possible that exchanges are pursued after transplant candidates explore and/or exhaust more conventional options. Recipients of deceased donations and exchanges tend to be older at the time of registration at 47-48 years old compared to direct living and anonymous recipients at 44-45, and surpassed only by patients who eventually die on the waiting list who register at 53 on average. Donors of transplants via exchange and anonymous donation are the oldest on average at 43-44 years old, followed by direct living donors and deceased donors at 37-40, which reinforces the notion that exchange recipients are in a more desperate position compared to those receiving direct living donations. If true, this suggests that there may not be much substitution occurring between direct living donations and exchanges.

[Insert Table 2 Here]

Table 3 presents the fraction of kidney grafts that survive at least one year, at least two years, the number of HLA mismatches between donor and recipient, and the duration of the waiting list registration. We see that graft survival is slightly higher for exchanges but very

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[12]Recall that the PRA score takes on a value of 0 to 100, and is interpreted to be the percentage of the general population with whom the patient is likely to be incompatible. Information on most recent PRA, both Class I and Class II which measure different HLA antibodies, only dates back to 2004 due to changes in PRA usage and data collection. Information on ending calculated PRA (C-PRA) begins in 2007. C-PRA is now the default measure used for deceased donor kidney allocation (Cecka, 2010).

similar across all living donor transplants for both one and two years at 96-97 percent and 93-94 percent, respectively.[13] One- and two-year graft survival is lower for recipients of deceased donor kidneys at 90 percent and 86 percent, respectively. Looking at the number of HLA mismatches by observed outcome, we see that direct living donations have the lowest number of HLA mismatches at 3.16 followed by deceased donations at 3.88. There is no difference in the average number of HLA mismatches across exchanges and anonymous donations at 4.31. Recipients of direct living donations have the shortest waiting list registration durations, roughly 237 days, followed by exchange at 468 days, anonymous at 654 days, and deceased donation at 813 days.[14] Both registration duration and number of HLA mismatches appear uncorrelated with graft survival among living donor kidney recipients after one and two years.

[Insert Table 3 Here]

4 Estimation

The first goal of this paper is to causally estimate the number of additional transplants generated by kidney exchanges. To this end, I estimate the effect of an increase in the probability of receiving an exchange transplant on the probability of experiencing one of the other registration outcomes. I will refer to these as the crowd-out or substitution estimates. I restrict estimation to observations corresponding to one of the following five outcomes: direct living, anonymous, exchange, or deceased donor transplant, or death on the waiting list. Each observation in the estimation sample takes on a value of 1 for one and only one of

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[13]Graft survival is defined for observations with a non-missing graft survival time in the OPTN STAR data. It takes on a value of 0 if the patient died before one or two years, or if there is a reported graft failure within one or two years. It takes on a value of 1 if the graft survival time exceeds one or two years, or if the patients' last known status is alive with a functioning kidney. The assumption is that these "lost" individuals would have returned to the system or they would have a death date reported through the Social Security Death Master File if their graft failed or they died. In order to ensure adequate time has passed for follow-up data, I restrict the analysis of one-year graft survival to transplants occurring on or before December 31, 2012, and December 31, 2011 for two-year graft survival.

[14]Note: roughly 1/3 of living donor kidney recipients never register for the waiting list. In these cases, registration duration is set to zero.

the five corresponding binary variables.

Using this framework, rather than a duration model that includes patients still waiting, allows me to account for the roughly 33 percent of patients who receive living donor transplants without registering and avoid problems caused by selection bias in who registers on the waiting list before transplant or death.[15] For many patients receiving a living donor transplant without first registering on the deceased donor waiting list, their search/waiting duration cannot be measured. Moreover, duration would not be well-measured if a substantial portion of patients only register on the waiting list *after* searching for a living donor.

I use a 2SLS approach to obtain the parameters of interest. The most important reason for doing so is that regressing a non-exchange binary registration outcome indicator on the indicator for transplant via exchange yields estimates completely driven by the observed shares of registration outcomes, and the estimates mathematically cannot be greater than zero. There are also possible reverse causality and selection issues; those who are sicker and less likely to find a living donor transplant may be more likely to seek out exchanges and may also experience worse transplant quality outcomes.

Consider the following set of reduced form specifications indexed by r for each registration outcome of interest:

$$Y_{rizt} = \theta_r Activity_{zt} + X_i\beta_r + \alpha_{rz} + \gamma_{rt} + \epsilon_{rizt}, \tag{12}$$

where Y represents the registration outcome of interest for individual i in zip code z in month t. *Activity* is a measure of local exchange activity to zip code z in the month of outcome t. X is a vector of observables for patient i, including race, gender, blood type, education, previous transplant status, PRA score, and age at listing.[16] I include a zip

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[15]Almost 26 percent of direct living, 6 percent of exchange, and 3 percent of anonymous transplants occurred without an associated waiting list registration, based on OPTN STAR data as of 12/31/2014. In fact, I find that patients receiving living donor transplants in areas with higher levels of *Activity* are less likely to register on the deceased donor waiting list beforehand.

[16]PRA is included as a categorical variable. First, I use the maximum reported PRA score among several available measures including current, most recent, peak, and ending PRA scores. I then convert this value into a 0 if it is between 0 and 10, 1 if it is between 10 and 20, ..., and 9 if it is between 90 and 100. Then, I

code fixed effect, α_{rz}, to control for any unobserved heterogeneity across zip codes where patients live that are correlated with local kidney exchange activity. Such factors might include average affluence, quality of nearby health care institutions, and proximity to higher education or other research institutions. I also include a month-year fixed effect, γ_{rt}, to control for nationwide transplantation trends and national-level policy shocks. ϵ_{rizt} is the idiosyncratic error term.

We can think of each θ as a difference-in-differences estimator where *Activity* measures treatment intensity. θ_r captures the effect of local exchange activity on Y_r, i.e. the effect of one additional local exchange transplant on the probability of experiencing the registration outcome corresponding to Y_r conditional on experiencing any transplant or death outcome. Rather than focus on each individual θ, the main focus of the estimation results will be the ratio of $\dfrac{\theta_k}{\theta_E}$, where θ_k is the effect of *Activity* on any non-exchange outcome k and θ_E is the effect of *Activity* on the probability of observing a transplant via exchange. A one percentage point increase in the probability of receiving an exchange transplant results in change of $\dfrac{\theta_k}{\theta_E}$ in the probability of experiencing outcome k; the set of these ratios yield the substitution estimates of interest.

I estimate the ratios of interest directly using 2SLS, where the first stage specification is:

$$Y_{Eizt} = \theta_E Activity_{zt} + X_i \beta_E + \alpha_{Ez} + \gamma_{Et} + \epsilon_{Eizt}. \tag{13}$$

The second stage specification is:

$$Y_{kizt} = \lambda_k \hat{Y}_{Eizt} + X_i \beta_k + \alpha_{kz} + \gamma_{kt} + \epsilon_{kizt}, \tag{14}$$

where Y_{kizt} is the non-exchange outcome variable, $\hat{Y}_{Eizt}$ is the predicted probability of ob-

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concatenate this with an index value corresponding to the PRA variable from which the maximum PRA score is obtained. So, for example, a value of 21 for the categorical variable would indicate that the individual's maximum PRA score comes from the second PRA variable and is between 10 and 20. Observations missing a PRA score are given their own category so that they are not excluded from the analysis.

serving a transplant via exchange obtained from estimating the first stage specification, and $\hat{\lambda}_k$ is simply $\dfrac{\hat{\theta}_k}{\hat{\theta}_E}$.

Next, I estimate how an increase in the probability of receiving an exchange affects the quality of transplant outcomes, conditional on receiving a transplant. I use the same method as outlined above. The first stage specification is the same as Equation (13). The second stage specification is:

$$Y_{qizt} = \lambda_q \hat{Y}_{Eizt} + X_i \beta_k + \alpha_{qz} + \gamma_{qt} + \epsilon_{qizt}, \tag{15}$$

where q now indexes the following quality outcomes: one-year graft survival, two-year graft survival, the number of HLA mismatches, and waiting list registration duration.[17] A one percentage point increase in the probability of receiving an exchange transplant results in change of $\dfrac{\theta_q}{\theta_E} = \lambda_q$ in quality outcome Y_q. Specifically, a one percentage point increase in the probability of receiving an exchange transplant results in a change of $\dfrac{\theta_{1yr}}{\theta_E} = \lambda_{1yr}$ percentage points in the probability of experiencing one-year graft survival, and similarly for two-year graft survival. A one percentage point increase in the probability of receiving an exchange transplant results in a change of $\dfrac{\theta_{HLA}}{\theta_E} = \lambda_{HLA}$ in the number of HLA mismatches of a transplant. Finally, a one percentage point increase in the probability of receiving an exchange transplant results in a change of $\dfrac{\theta_{duration}}{\theta_E} = \lambda_{duration}$ in registration duration measured in days.

4.1   Measuring Activity

The estimation strategy exploits variation in kidney exchange activity across location and time in order to estimate the effect of kidney exchanges on patient outcomes. This approach is similar to the one used by Currie and Moretti (2003) where they use local college openings as an instrument for maternal education. *Activity* is measured using the number of exchanges

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[17]Waiting list registration duration is set to 0 for the living donor transplant recipients who do not register on the deceased donor waiting list.

that occurred at transplant centers within 50 miles of a patient's zip code of residence in the month of the patient's transplant or death. I adjust this measure downward by one if I observe that the given patient received an exchange within 50 miles.[18] This measure reflects both the potential of local transplant centers to perform exchanges and the realization of that potential. Since patients and donors must be able to travel to transplant centers for testing and eventual transplant procedures, *Activity* reflects patient access to exchange and, consequently, is correlated with the probability of a patient receiving an exchange transplant.

I use 50 miles as the radius based on the percentiles presented in Table 4. Most patients who receive transplants do so within 50 miles of their home zip code - between 60 and 70 percent overall.[19] Figure 7 shows the average monthly number of exchanges performed within 50 miles for individuals in the sample over time and observed registration outcome. We see that this number ranges from 0 to 2.75, and tends to be higher for recipients of exchanges and anonymous donations.

[Insert Table 4 Here]

[Insert Figure 7 Here]

To be valid, *Activity* must be exogenous to the dependent variables of interest; it cannot affect non-exchange outcomes directly or through an omitted variable, nor have a reverse causal relationship with the the non-exchange outcomes. The inclusion of zip code and month fixed effects control for any national trends and time-invariant differences across locations in the dependent variables. The main threat to the exogeneity of *Activity* is whether transplant centers adopt and promote exchange as a transplant option in response to local demand for exchange and idiosyncratic pre-trends in the dependent variables of interest. For example,

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[18]I use GIS mapping software along with the zip codes of patients and transplant centers to determine which transplant centers are within 50 miles of the centroid of each observed patient zip code. I then aggregate over these nearby centers to determine how many transplants via kidney exchange occurred each month within the 50 mile radius.

[19]I test the robustness of the following analysis to the use of different radii and present the results in Section 6.

we may be concerned that transplant centers in areas experiencing worsening outcomes, such as declining direct living donations, are more likely to adopt and promote exchange.

However, the presence of a "champion" - a particular leader or small group of individuals working at a given transplant center who want to implement the new methodology - appears to be the driving force behind effective exchange adoption and promotion. For example, Garet Hil created the National Kidney Registry, a paired exchange consortium, after his daughter had to endure a "difficult and extensive donor search" (NKR, 2015). In addition to having a champion, centers with active exchange programs appear to be those with the resources necessary for such an undertaking. Conversations with Alan Leichtman, a prominent nephrologist who initiated the paired kidney donation program at the University of Michigan in 2008, support the importance of these two criteria.

University hospitals are likely candidates to have a champion and the resources needed; 13 of the 20 most active kidney exchange centers are at university medical centers based on the number of exchanges performed between January 2000 and July 2014. The most active centers include Johns Hopkins Hospital, Methodist Specialty and Transplant Hospital, University of Michigan Medical Center, Northwestern Memorial Hospital, University of Maryland Medical System, and UCLA Medical Center.[20] While this observation may raise concerns that centers with sufficient resources to start or participate in exchange programs tend to be in areas that experience systematic differences in patient outcomes, the inclusion of zip code fixed effects should substantially alleviate this concern.

Recall that exchange appears to be a transplant option people pursue after realizing their weak prospects of a timely deceased donation or direct living donation. If transplant centers adopt and promote exchanges in response to local demand, we would expect to see worsening outcomes lead to increases in future exchange activity. I test this and discuss the results in Section 6 and Appendix B. The only statistically significant results suggest that declining rates in deaths while waiting, which is an improving outcome, are correlated with increases

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[20]Based on OPTN STAR data as of 12/31/2014.

in future exchange activity. I find no evidence that worsening outcomes are correlated with future exchange activity.

A secondary concern with this identification strategy is that patients endogenously move from areas of low exchange activity to areas of higher exchange activity in pursuit of a transplant via exchange. While I cannot perfectly observe patients' moving behavior, I can observe whether patients changed zip code of residence between the time they register on the deceased donor waiting list and receive a kidney transplant. I analyze whether exchange activity near patients' current zip code at time of transplant predicts a change in zip code, whether exchange activity near patients' original (listing) zip code at the time of transplant predicts a change in zip code, and whether the *Activity* differential between patients' current and original zip code is correlated with the type of transplant received. The results, which are presented in Table 9 and discussed further in Appendix B, suggest that patients do not decide to change their zip code of residence based on local exchange activity levels. They also suggest that the *Activity* differential among movers is not correlated with the type of transplant received.

5 Results

Table 5 presents the estimates of how the probability of receiving a kidney exchange affects one's probability of receiving a direct living, anonymous, or deceased donor kidney, as well as death on the waiting list, conditional on experiencing one of these five outcomes. The first column presents the first stage results, which correspond to $\hat{\theta}_E$ in the previous section: the effect of nearby exchange activity in the month of a patient's registration outcome on the probability that the patient receives a kidney via exchange. The estimate of $\hat{\theta}_E$ implies that one additional exchange transplant within 50 miles of a patient increases that patient's probability of receiving an exchange transplant by 40 percent.[21] This estimate is highly

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[21]The estimated effect of one additional exchange transplant is a 0.56 percentage point increase in the probability of receiving a transplant via exchange. The overall probability of receiving a transplant via exchange in the estimation sample is 1.4 percentage points.

significant, further confirming the importance of proximity to exchange activity with respect to obtaining a transplant via exchange.

[Insert Table 5 Here]

The second through fifth columns present the substitution estimates, which correspond to the different $\hat{\lambda}_k$. The second column shows statistically significant reduction of 0.5 percentage points in the probability of receiving a direct living transplant associated with a one percentage point increase in the probability of receiving a kidney exchange. This estimate implies that 5 of every 10 transplants via exchange would have been direct living donor transplants in the absence of exchange, which is essentially identical to the substution rate implied by the simulations in Roth et al. (2004).

The third column shows a statistically significant increase of 0.12 in the probability of receiving an anonymous donation with a one percentage point increase in the probability of receiving an exchange. This suggests that for every 10 transplants via exchange 1.2 additional people decide to donate anonymously. This anonymous donor crowd-in effect is a new finding; prior simulations rely on fixed pools of representative patient-donor pairs and therefore cannot account for the crowd-in of donors from outside of the selected pool. Taken together with the second column estimate, this suggests that $10 - 5 + 1.2 = 6.2$ of every 10 transplants via exchange represent living donor transplants that would not have occurred in the absence of exchange.

The fourth column shows that the probability of receiving a transplant via exchange has a statistically insignificant negative effect of -0.09 on the probability of receiving a deceased donor kidney. As discussed in Section 2, it is likely that any relationship between these two probabilities is based on the allocation of deceased donor kidneys shifting to areas with less kidney exchange prevalence, rather than a reduction in the number of deceased donor organ transplants.

Finally, the fifth column shows a statistically significant relationship between exchange and death on the waiting list; a one percentage point increase in the probability of receiving

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a kidney exchange decreases the probability of dying on the waiting list by a 0.54 percentage points. This suggests that every 10 exchange transplants reduce deaths among those waiting by 5.4.

From Table 5, it is clear that exchanges increase the number of living donor transplants. Table 6 presents what the introduction of exchange means for graft survival, the number of HLA mismatches, and the duration of waiting list registrations ending in transplant. The first column shows that a ten percentage point increase in the probability of receiving an exchange statistically significantly increases the probability of one-year graft survival by 2 percentage points, or 2.2 percent relative to average one-year survival of 93 percent. The second column shows a smaller statistically significant increase in two-year graft survival: 1.9 percentage points, or 2.2 percent relative to average two-year survival of 88 percent.

[Insert Table 6 Here]

The third column shows the effect of exchange introduction on HLA mismatches, one possible mechanism through which graft survival could improve (Opelz, 1997). The estimate shows that the introduction of exchange has a positive but statistically insignificant effect on the number of HLA mismatches. Recall that Roth et al. (2004) find large reductions in HLA mismatches as exchanges are introduced; this is partially driven by patients choosing exchange over direct donation on the basis of HLA mismatches and donor age only, which does not appear to hold in reality. While exchange may enable patients to find closer matches, patients may also be willing to accept a slightly worse match instead of having to rely on a compatible family member, for example, who may be a much closer match. Moreover, if most of those receiving kidney exchanges are harder-to-match individuals and would not have received a transplant otherwise, then we would expect their transplants to push up the average number of HLA mismatches.

Finally, the fourth column shows the effect of exchange introduction on registration duration, another mechanism through which graft survival could improve (Meier-Kriesche et al., 2002). A ten percentage point increase in the probability of receiving an exchange reduces

registration duration by 59.2 days, or 10 percent relative to the registration duration average of 597 days. The result is clear; patients find transplants more quickly when exchanges are introduced. Part of this is likely due to the increase in living donor transplants, where the registration durations are much shorter than the wait for a deceased donor kidney. It is also likely that reduced search frictions and reduced excess demand for deceased donor kidneys contribute to this effect, though there is no clean way to isolate these different components.

6   Robustness

In this section, I briefly address the estimation of alternative specifications in order to test the robustness of the 2SLS results. Appendix B expands on this discussion, and also further addresses concerns raised in Section 4.1 surrounding the validity of *Activity* as an instrument.

First, we may worry about reverse causality in the first stage regression. Since paired exchanges often involve at least two patients being transplanted simultaneously, sometimes at the same transplant center, a patient receiving an exchange will sometimes imply the occurrence of at least one other exchange in the same month at a nearby center. There may also be issues caused by reverse causality in the anonymous donation regression. Since anonymous donations can facilitate donor chains, an additional transplant via anonymous donation may cause an increase in the level of nearby exchanges performed in the same period. To address this, I estimate two specifications using lagged measures of *Activity*: one with one- and two-month lags of *Activity* as instruments, and one with a six-month lagged total of exchange activity. While the magnitudes of the results change slightly, they show the same pattern of (less precise) results as the original estimates (see Table 10).

Second, we may wonder if the results are robust to zip-code aggregation, which overcomes the weakness inherent in excluding those who are still waiting for a kidney from the substitution analysis. While the results from this exercise suggest that 0.7 of every 10 recipients of kidney exchanges would either still be waiting, or would have exited the waiting list for some reason other than transplant or death, the results still imply that 6.1 of every 10 exchanges

represent new living donor transplants.

Third, we may be curious about the sensitivity of the results to using different mileage radii in determining the level of nearby activity. The results from alternate specifications using 30 and 75 mile radii, as opposed to a 50 mile radius, also largely show the same pattern of results. The largest difference is that these alternate specifications imply even larger gains in living donations of 8 and 7.6 of every 10 exchanges, respectively, though these estimates are not statistically different from the original results.

Finally, we may question the robustness of the substitution analysis to the inclusion of patients removed from the waiting list due to being too sick to transplant, or those who refused transplants offered to them. The results from this exercise are very similar to the original estimates, implying that 6 of every 10 exchanges represent new living donor transplants.

7 Conclusion

As of December 15, 2016, 100,852 candidates are waiting for a kidney (OPTN, 2016). The growing shortage of transplantable organs has driven economists, transplant practitioners, and lawmakers to develop creative solutions. The innovation of transplantation among patients with incompatible willing donors via exchange has grown in popularity in recent years, facilitated by single-center registries and consortia of transplant centers using computer-optimized matching mechanisms.

Evaluating the extent to which exchange improves observed patient outcomes is the most direct way of evaluating efforts to introduce and promote this mode of transplantation. Such an analysis is more feasible now with the growing prevalence of exchange. This paper is the first to undertake such an evaluation beyond the use of simulations. I use administrative data on waiting list registrations and transplants, which contain a rich set of patient and transplant center characteristics. To identify the effects of interest, I construct a novel measure of time-varying local exchange activity using patient and transplant center location

data.

The evidence presented in this paper suggests that kidney exchange programs are highly effective in increasing the number of transplants, such that 6.2 of every 10 transplants via exchange represent living donor transplants that would not have occurred in the absence of exchange. This finding is especially important given that many patients receiving exchange transplants are hard to match and face significant risk of dying while waiting for a compatible deceased donor kidney. Of the 6.2 new transplants, 1.2 come from anonymous altruistic donors who are now able to facilitate many more transplants with a single kidney donation and more willing to donate as a result. To date, there have been 5,937 transplants performed via exchange (OPTN, 2016). The results of this paper suggest that 3,681 of those represent living donor kidney transplants that would not have happened in the absence of exchange.

In addition to creating many additional living donor transplants, the evidence presented in this paper suggests that the increasing prevalence of exchange has a significant impact on transplant quality outcomes. Conditional on receiving a transplant of any kind, a ten percentage point increase in the probability of receiving a transplant via exchange is shown to increase average one-year graft survival by 2 percentage points, two-year graft survival by 1.9 percentage points, and reduces registration duration by 59.2 days, relative to an average overall one-year graft survival rate of 93 percent, two-year rate of 88 percent, and 597 day registration duration. These results are in line with what we would expect given that exchanges increase the number of living donor transplants performed.

The net increase in social welfare from a single living donor transplant ranges from an estimated $473,000 (Schnier et al., 2014, based on Matas and Schnitzler, 2004) to $1.1 million (Held et al., 2016) depending on the gain in quality-adjusted life-years (QALY), value of a QALY, and the cost savings of living donor transplantation compared to continued dialysis.[22] The cost savings alone range from roughly $125,000 in 2014 U.S. dollars (based on Matas and Schnitzler's $94,579 in 2002 U.S. dollars) to $195,000 (Held et al., 2016), an estimated

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[22]Note, however, that these estimates do not appear to account for costs incurred by living donors.

75 percent of which represents savings to taxpayers (Held et al., 2016). A high-end estimate of the additional costs of facilitating an exchange transplant is $6,000 based on transplant centers' costs of joining and using the services of the National Kidney Registry to facilitate exchanges (Melcher et al., 2012).

Focusing only on the quantity effects of exchange on living donor kidney transplants, the estimated cost reductions and net social welfare gains are staggering. Every 10 transplants via exchange generate an estimated net social welfare gain of $2.87 million to $6.81 million,[23] amounting to a total of $1.7 to $4 billion for all 5,937 exchange transplants. Focusing only on the cost savings, every 10 exchange transplants reduce health care costs by an estimated $715,000 to $1.15 million, amounting to a total of $425 to $682 million, 75 percent of which accrues to U.S. taxpayers.

The findings of this paper should therefore be highly encouraging to transplant centers considering or already performing kidney exchanges. The results should also encourage lawmakers and the United Network for Organ Sharing to further promote exchange as a transplant option. This policy implication is bolstered by research from Roth and coauthors demonstrating the increasing returns to scale associated with larger registries of incompatible pairs.

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[23]Sample calculation: $(\$473,000x6.2) - (\$6,000x10) = \$2.87$ million per 10 exchange transplants.

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Appendix A Proofs

A.1 Proof for Proposition 1

Proposition 1. *If the introduction of exchange does not affect the costs nor the benefits to L of direct donation, i.e. $C^E(Direct) = C^N(Direct)$ and $B_k(Q^E(Direct)) = B_k(Q^N(Direct))$, then L is less likely to choose direct donation over no donation after the introduction of exchange.*

Proof. This result holds because patient k's outcome does not improve with exchange introduction under direct donation, while k's expected outcome does improve when k's prospective donor, L, does not donate. L will donate directly when $U_L(Direct) \geq U_L(None)$, or

$$U_L(Direct) = B_k(Q(Direct)) - C(Direct) \geq B_k(Q(None)) = U_L(None). \quad (16)$$

If $U_L(None)$ increases more than $U_L(Direct)$ when exchange is introduced, then $\mathrm{Prob}[U_L(Direct) \geq U_L(None)]$ will decrease.

Given that exchange introduction has no effect on the cost of donating directly, nor the benefit that L derives from donating to patient k, the effect of exchange introduction on the utility derived from each choice is given by the following:

$$\Delta U_L(Direct) = [B_k(Q^E(Direct)) - C^E(Direct)] - [B_k(Q^N(Direct)) - C^N(Direct)] = 0 \quad (17)$$

and

$$\Delta U_L(None) = \Delta B_k(Q(None)). \quad (18)$$

If patient k's expected outcome improves with the introduction of exchange when L does not donate, such that

$$\Delta U_L(None) = \Delta B_k(Q(None)) \geq 0 = \Delta U_L(Direct), \quad (19)$$

then L is less likely to donate directly, relative to not donating at all, after the introduction of exchange. □

A.2 Proof for Proposition 2

Proposition 2. *Suppose again that the introduction of exchange does not affect the costs nor the benefits to L of direct donation, i.e. $C^E(Direct) = C^N(Direct)$ and $B_k(Q^E(Direct)) = B_k(Q^N(Direct))$. Then a representative prospective donor L is more likely to become a living kidney donor if the introduction of exchange increases the net utility of donating via exchange, relative to not donating, by a larger magnitude than it increases L's reservation utility, i.e. $[U_L^E(Exch) - U_L^E(None)] - [U_L^N(Exch) - U_L^N(None)] > U_L^E(None) - U_L^N(None)$.*

Proof. L is more likely to become a living kidney donor - that is, the increased likelihood of donating via exchange outweighs the decreased likelihood of donating directly - if

$$\Delta U_L(Exch) - \Delta U_L(None) > -[\Delta U_L(Direct) - \Delta U_L(None)]. \tag{20}$$

This becomes:

$$[U_L^E(Exch) - U_L^N(Exch)] - [U_L^E(None) - U_L^N(None)] >$$
$$- \{[U_L^E(Direct) - U_L^N(Direct)] - [U_L^E(None) - U_L^N(None)]\}. \tag{21}$$

Recall the following relationship from equation 17:

$$\Delta U_L(Direct) = B_k(Q^E(Direct)) - B_k(Q^N(Direct)) - C^E(Direct) + C^N(Direct) = 0. \tag{22}$$

This implies that equation (21) reduces to:

$$[U_L^E(Exch) - U_L^N(Exch)] - [U_L^E(None) - U_L^N(None)] > [U_L^E(None) - U_L^N(None)]. \tag{23}$$

The last step is a simple rearrangement of terms for interpretation purposes:

$$[U_L^E(Exch) - U_L^E(None)] - [U_L^N(Exch) - U_L^N(None)] > [U_L^E(None) - U_L^N(None)]. \quad (24)$$

Alternatively, for interpretation purposes, we can substitute in the terms for each utility and rearrange. We then obtain:

$$MB_L^E + MS_L^E - MB_L^N - MS_L^N - \Delta C(Exch) > \Delta B_k(Q(None)) \quad (25)$$

or

$$\Delta MB_L + \Delta MS_L - \Delta C(Exch) > \Delta B_k(Q(None)). \quad (26)$$

MB (MS) represents marginal benefit (marginal surplus) of donating via exchange over not donating at all, $\Delta C(Exch)$ represents the change in cost of donating via exchange before and after introduction, and $\Delta B_k(Q(None))$ is the change in benefit L derives from k's well-being following exchange introduction. □

A.3   Proof for Proposition 3

Proposition 3. *If the cost of donating anonymously is unaffected by the introduction of exchange, i.e. $C^E(Anon) = C^A(Anon)$, then individuals without a loved one in need of a kidney will be more likely to donate anonymously to start a donor chain and less likely to donate anonymously to a single patient following the introduction of exchange.*

Proof. Potential donor A will donate anonymously when

$$U_A(Anon) = S_i(Q(Anon)) - C(Anon) \geq 0 = U_A(Anon). \quad (27)$$

If $U_A(Anon)$ increases when exchange is introduced, then $\text{Prob}[U_L(Anon) \geq 0]$ will increase.

The effect of exchange introduction on the utility derived from donating anonymously is

given by the following:

$$\Delta U_A(Anon) = U_A^E(Anon) - U_A^N(Anon) =$$

$$S_i(Q^E(Anon)) - S_i(Q^N(Anon)) + S_{-i}(Q^E(Anon)) - [C^E(Anon) - C^N(Anon)] \quad (28)$$

or

$$\Delta U_A(Anon) = \Delta S_i(Q(Anon)) + S_{-i}(Q^E(Anon)) - \Delta C(Anon). \quad (29)$$

If the cost of donating anonymously is the same whether or not exchange has been introduced (i.e. $\Delta C(Anon) = 0$), then $\Delta C(Anon)$ drops out implying that A will be at least as likely to donate anonymously following the introduction of exchange if

$$\Delta S_i(Q(Anon)) + S_{-i}(Q^E(Anon)) \geq 0. \quad (30)$$

This condition says that A will be more likely to donate anonymously if the introduction of exchange increases the total surplus that A's donation generates for patients in need of transplants. Now, since the introduction of exchange improves patients' outside options, it is likely that $\Delta S_i(Q(Anon)) < 0$. If, after the introduction of exchange, anonymous donations are not shifted toward the use of starting exchanges via donor chains, then we would expect a reduction in anonymous donations. However, if A's donation facilitates at least one transplant beyond i's (the direct recipient), then the additional surplus is very likely to outweigh the small negative effect of exchange on the surplus generated by A's donation to i. □

Appendix B   Robustness Checks

I first test whether current outcome measures appear to affect future levels of local exchange activity. Tables 7 and 8 present the results from fitting the data to equation (12) while including several leads and lags of *Activity*. Figures 8 and 9 plot these results graphically. I

include 12 months of leads and lags, and consolidate them into two-month averages to help smooth out monthly volatility. I then perform joint F-tests of the statistical significance of all of the leads in each specification. Death on waiting list is the only outcome for which I find evidence of an outcome variable affecting future values of *Activity*. The result suggests that a relative decline in deaths on the waiting list corresponds to future increases in local exchange activity, and suggests that the estimated reduction in deaths while waiting due to exchange could be overstated. However, this result is the opposite of what we would expect if centers were adopting and promoting kidney exchanges in response to worsening outcomes. Combined with the results from the tests of the quality outcome measures, it does not appear that local exchange activity is endogenous to trends in patient outcomes.

[Insert Tables 7 and 8 Here]

[Insert Figures 8 and 9 Here]

Next, I test whether patients endogenously move or change zip code of residence in order to pursue exchange transplants. To start, I can observe patients' zip codes of residence at the time of registration on the deceased donor waiting list and again when they receive a transplant. However, I cannot perfectly observe whether patients engage in such behavior because (1) not all patients receiving living donor transplants register on the deceased donor waiting list and (2) I do not observe an updated zip code for patients who died while waiting. With these limitations in mind, I analyze whether exchange activity near patients' current zip code at time of transplant predicts a change in zip code, whether exchange activity near patients' original (listing) zip code at the time of transplant predicts a change in zip code, and whether, conditional on observing a change in zip code, the *Activity* differential between patients' current and original zip code is correlated with the type of transplant received.

First, I find that patients receiving a direct living donor transplant are the least likely to change zip codes (9.3 percent), while patients receiving a deceased donor transplant are the most likely to change zip codes (16.4 percent). Exchange and Anonymous donor recipients

are in the middle at 11.8 percent and 14.8 percent, respectively. Despite these differences, however, there appears to be no relationship between exchange activity and moving behavior. Column 1 of Table 9 suggests that patients living in more exchange-active zip codes at the time of transplant are no more likely to have changed zip codes than patients living in less exchange-active zip codes. Similarly, column 2 suggests that the level of exchange activity at time of transplant in a patient's original (listing) zip code is not correlated with whether that patient changed zip codes. Finally, columns 3 through 6 suggest that, among patients who changed zip codes, the differential in exchange activity between their current and original zip codes is not correlated with the type of transplant received.

[Insert Table 9 Here]

To address concerns of reverse causality resulting from the use of current-period nearby exchange activity measures, I replicate the results from Tables 5 and 6 using lagged measures of *Activity*. The first specification includes one- and two-month lags, while the second specification uses the six-month lagged total. Anonymous donations and exchanges can only facilitate current or future transplants via exchange, hence the use of lags to avoid the reverse causality issue. However, lags also reduce the precision of the estimates of interest. The second and third row of results in Tables 10 and 11 present the results from this exercise. We see that the estimates of direct living crowd-out is close to the original 2SLS estimate at -0.68 and -0.61, respectively. The estimate of anonymous donor crowd-in becomes roughly twice the magnitude of the original at 0.21 and 0.28, respectively. The deceased donor substitution estimate turns positive and is statistically significant in the six-month lagged total specification, though this again is likely due to geographical shifting rather than a large deceased donor crowd-in effect. Finally, the statistically significant reduction of deaths on the waiting list roughly doubles in magnitude in both specifications to -1.02 and -1.26, respectively.

[Insert Tables 10 and 11 Here]

The estimates of direct living crowd-out and anonymous crowd-in are the most important for determining the change in the overall number of transplants. Together, these estimates imply that 5.3 (6.7 for six-month lagged total) of every 10 transplants via exchange represent an increase to the number of transplants performed. These estimates straddle the original estimate of 6.2, but are not statistically distinguishable from one another. As for the quality results, we see that the graft survival estimates decrease, the magnitudes of the HLA mismatch estimates straddle the original, and registration duration estimates increase somewhat dramatically in magnitude. However, the results using lagged exchange activity are still encouraging in that the one-year graft survival estimate is positive in both specifications, the two-year graft survival estimate is positive in the six-month lagged total specification, there is still a small positive but insignificant effect on HLA mismatches in both specifications, and there is still a significant reduction in registration duration in both specifications.

Next, I test whether the original 2SLS substitution results are sensitive to aggregation to the zip code month level. The original 2SLS results relate the probability of receiving an exchange to the probability of experiencing the other registration outcomes. Note that all the substitution effects of exchange on the other registration outcomes sum to -1 when using registration-level data; this reflects the implicit assumption that every exchange would have resulted in one of the other four outcomes in the absence of exchange. Aggregating yields a more direct unit-measure of the number of additional transplants performed as a result of the introduction of kidney exchange, rather than inferring it from changing probabilities. Such aggregation allows more flexibility in the estimates and can provide insight into how many individuals receiving an exchange would have continued to wait for a transplant.

Zip code month is the most natural aggregation level given the preceding analysis, and still allows for the use of nearby exchange activity based on zip code. Analogous to the modification made when using registration-level data, I subtract the number of within-50-miles exchange transplants received by patients in a particular zip code month from the nearby activity measure for that particular zip code month observation. The fourth row

of Table 10 presents the results from this test, which are very similar to the original 2SLS results.

Notice that the substitution effects no longer sum to -1, but they do come very close at -0.93. This suggests that 0.7 of every 10 exchange recipients would have continued to wait for a kidney rather than experience one of the other four well-defined outcomes. The crowd-out of direct living donors is nearly identical at -0.52 compared to -0.5, the crowd-in of anonymous donors is 0.13 compared to 0.12, the substitution away from deceased donor transplants is smaller in magnitude and still statistically insignificant at -0.039, and the reduction in deaths on the waiting list is slightly smaller in magnitude at -0.5 compared to -0.54. These estimates imply that $10 - 5.2 + 1.3 = 6.1$ of every 10 exchanges are living donor transplants that would not have occurred in the absence of exchange, which is again very similar to the original estimate of 6.2.

Now I turn to the question of whether the results from Section 5 are sensitive to the use of different mileage radii in determining the level of local exchange activity. The fifth row of Table 10 also presents the substitution results when using a 30 mile radius instead of 50 miles. The results show a small reduction in the crowd-out estimate for direct living transplants, larger crowd-in of anonymous donations, larger substitution away from deceased donor transplants but still statistically insignificant, and almost no change in the negative effect on deaths on the waiting list. The changes in the effect of *Activity* on anonymous and deceased donations are the most notable, while the first stage estimate barely changes. The fourth row of Table 11 presents the effects on graft survival, HLA mismatches, and registration duration when using a 30 mile radius. These results are virtually identical compared to the original 2SLS estimates, except for a slight attenuation of the effect on registration duration. The observed differences suggest that the probability of receiving an anonymous donor transplant is more heavily influenced by exchange activity within 30 miles than activity 30 to 50 miles away. It is possible that the supply of deceased donor kidneys is much more responsive to immediate local exchange activity. However, it is more likely that

the estimate picks up regional shifts in allocation when a smaller radius is used, which is a more coherent explanation given the similarity of these results and the original 2SLS results.

Row six of Table 10 presents the substitution results when using a 75 mile radius instead of 50 miles. Again, these results are similar to the original 2SLS results. The effect of exchange on direct living donations becomes slightly smaller in magnitude, and a there is a slight increase in the magnitude of the effects on deceased donor transplants and deaths on the waiting list. The fifth row of Table 11 presents the effects of exchange the quality measures when using a 75 mile radius. Again, these results are very close to the original 2SLS results, with slight attenuation in the effects on graft survival and registration duration.

Finally, I test the robustness of the original 2SLS substitution results to the inclusion of patients removed from the waiting list as a result of being too sick to transplant, and those removed as a result of refusing transplant offers. In my estimation sample, 25,952 patients were removed from the waiting list for these reasons, 15 percent of whom refused a transplant and 85 percent of whom were deemed too sick to transplant. The results, presented in the seventh row of Table 10 are nearly unchanged: 5.3 of every 10 exchanges would have been a direct living transplant, 1.3 additional anonymous donations occur for every 10 exchanges, there is a statistically insignificant change in deceased donor transplants, and a there is a significant reduction in deaths while waiting of 6.2 for every 10 exchanges. Similarly, the gain in living donations is relatively unchanged: $10 - 5.3 + 1.3 = 6$ of every 10 transplants via exchange represent new living donor transplants using this specification.

Table 1: Frequency of Registration Outcomes

Observed Outcome	2000 - July 2014		2007		2013	
	N	Percent	N	Percent	N	Percent
Exchange	4,103	1.39	202	0.96	753	3.52
Anonymous	1,528	0.52	97	0.46	176	0.82
Direct Living	82,844	27.99	5,720	27.04	4,786	22.37
Deceased	145,408	49.13	10,591	50.08	11,164	52.19
Died on WL	62,064	20.97	4,540	21.47	4,512	21.09
Total	**295,947**		**21,150**		**21,391**	

Source: OPTN STAR Data as of 12/31/2014.

Note: Includes all transplants where donor relationship is observed, and deaths of those registered on the deceased donor waiting list.

Table 2: Sensitivity and Age (2000 - July 2014)

Observed Outcome	Most Recent PRA (Class I)*	Most Recent PRA (Class II)*	Ending C-PRA**	Age at Listing***	Donor Age
Exchange	15.02	14.50	22.10	46.56	43.05
SD	(27.64)	(28.02)	(34.29)	(14.47)	(11.56)
N	3,636	3,481	3,516	4,103	4,103
Anonymous	8.57	8.66	16.68	44.56	43.67
SD	(20.69)	(22.28)	(30.22)	(15.29)	(11.82)
N	1,193	1,106	1,017	1,528	1,528
Direct Living	5.71	5.28	8.98	44.15	40.68
SD	(16.85)	(16.98)	(22.33)	(16.05)	(11.23)
N	52,167	46,053	30,048	82,844	82,843
Deceased	10.93	9.63	19.66	47.82	37.49
SD	(24.54)	(23.68)	(33.23)	(15.25)	(16.71)
N	99,787	89,321	72,104	145,407	145,408
Died on WL	-	-	23.32	52.85	-
SD	-	-	(37.35)	(12.25)	-
N	0	0	32,208	64,825	0
Total	9.27	8.31	18.24	47.86	38.76
SD	(22.48)	(21.94)	(32.67)	(15.19)	(14.98)
N	156,783	139,961	138,893	298,707	233,882

Source: OPTN STAR Data as of 12/31/2014.
*These values are missing for those who were not transplanted. Due to changes in data collection, values only reported from 2004 onward.
**Due to changes in data collection, values only reported from late 2007 onward
***For those transplanted without ever having listed, this is the age at time of transplant.

Table 3: Survival, Match Quality, Waiting Time (2000 - July 2014)

Observed Outcome	Graft Survival >1 year*	Graft Survival >2 years*	# of HLA Mismatches	Registration Duration (Days)**
Exchange	0.97	0.94	4.31	467.68
SD	(0.18)	(0.23)	(1.25)	(523.69)
N	2,995	2,300	4,030	4,099
Anonymous	0.96	0.93	4.31	654.10
SD	(0.20)	(0.26)	(1.26)	(606.73)
N	1,261	1,097	1,497	1,528
Direct Living	0.96	0.93	3.16	237.47
SD	(0.20)	(0.26)	(1.66)	(346.70)
N	75,348	70,610	82,097	82,698
Deceased	0.90	0.86	3.88	813.43
SD	(0.29)	(0.35)	(1.75)	(717.70)
N	127,580	116,714	144,482	145,153
Total	0.93	0.88	3.64	602.31
SD	(0.26)	(0.32)	(1.74)	(667.25)
N	207,184	190,721	232,106	233,478

Source: OPTN STAR Data as of 12/31/2014.
1) Note that survival, HLA mismatches, and registration duration are only defined for transplant recipients.
*One-year graft survival excludes 2013-14 data, two years excludes 2012-14.
**Duration is 0 for living donor kidney recipients who did not register on the waiting list.

Table 4: Patient Distance to Transplant Center of Operation

Percentile	All	Exchange	Anonymous	Direct Living	Deceased
10	4.12	5.63	4.38	4.85	3.74
20	7.30	9.79	7.34	8.49	6.65
30	11.09	13.79	10.76	12.62	10.16
40	16.05	21.00	14.66	18.07	14.82
50	24.01	29.75	21.11	26.10	22.49
60	36.07	43.71	31.89	38.45	34.53
70	56.21	65.36	49.59	58.74	54.45
80	86.93	103.21	81.10	93.05	83.40
90	146.22	193.37	182.88	163.57	137.81
N	231,796	4,070	1,514	82,019	144,193

Source: OPTN STAR Data as of 12/31/2014.

Table 5: Measuring Substitution, 2SLS Results

VARIABLES	Exchange (First Stage)	Direct Living	Anonymous	Deceased	Died on WL
Total Exchanges Nearby (Excluding Own if Relevant)	0.0056*** (0.00034) [0.014]				
Exchange Indicator (2SLS Estimates)		-0.50*** (0.11) [0.28]	0.12*** (0.031) [0.0052]	-0.086 (0.13) [0.49]	-0.54*** (0.093) [0.21]
Observations	291,995	285,601	285,601	285,601	285,601
Number of Zip Codes	26,250	19,856	19,856	19,856	19,856

Clustered standard errors in parentheses (at zip code level)
*** p<0.01, ** p<0.05, * p<0.1
Means of dependent variables in brackets
1) Regressions include month-year fixed effects, zip code fixed effects, as well as controls for age at listing, PRA, previous transplant status, blood type, gender, race, education.

Table 6: Quality Measures, 2SLS Results

VARIABLES	Graft Survival >1 year	Graft Survival >2 years	HLA Mismatches	Registration Duration (Days)
Exchange Indicator (2SLS Estimates)	0.20*** (0.066) [0.93]	0.19* (0.097) [0.88]	0.40 (0.38) [3.64]	-592*** (170) [597]
Observations	198,296	181,901	223,184	224,536
Number of Zip Codes	17,685	17,165	18,428	18,455
	First Stage Results: Dependent Variable is Exchange Indicator			
Total Exchanges Nearby (Excluding Own if Relevant)	0.0073*** (0.00050) [0.015]	0.0073*** (0.00060) [0.012]	0.0072*** (0.00044) [0.017]	0.0072*** (0.00044) [0.018]
Observations	204,849	188,456	229,657	231,015
R-squared	0.026	0.023	0.026	0.027
Number of Zip Codes	24,238	23,720	24,901	24,934

Clustered standard errors in parentheses (at zip code level)
*** p<0.01, ** p<0.05, * p<0.1
Means of dependent variables in brackets
1) Regressions include month-year fixed effects, zip code fixed effects, as well as controls for age at listing, PRA, previous transplant status, blood type, gender, ethnicity, education.
2) The non-death-censored graft survival variables also assume transplant survival for those whose last known status is alive with a functioning kidney transplant.
3) One-year graft survival excludes 2013-14 data, two years excludes 2012-14.

Table 7: Leads and Lags of *Activity*, Substitution

VARIABLES	Direct Living	Anonymous	Deceased	Died on WL
11-12 Month Lag	0.00017	-0.00045*	0.0015	-0.00082
	(0.0010)	(0.00024)	(0.0012)	(0.00080)
9-10 Month Lag	0.00049	-0.00011	-0.0012	0.0012
	(0.0011)	(0.00028)	(0.0012)	(0.00083)
7-8 Month Lag	0.0010	-0.000029	0.000044	-0.00082
	(0.0010)	(0.00027)	(0.0012)	(0.00080)
5-6 Month lag	-0.0015	0.00073***	0.0013	-0.0011
	(0.0010)	(0.00026)	(0.0012)	(0.00082)
3-4 Month Lag	-0.00020	0.00023	0.00091	-0.0015*
	(0.0010)	(0.00025)	(0.0012)	(0.00079)
1-2 Month Lag	-0.0015	-0.00016	0.00072	0.00075
	(0.00099)	(0.00022)	(0.0012)	(0.00078)
Total Exchanges Nearby	-0.0026***	0.00040**	-0.0021**	-0.0012**
(Excluding Own if Relevant)	(0.00074)	(0.00020)	(0.00088)	(0.00058)
1-2 Month Lead	0.00093	0.00012	-0.00015	-0.00100
	(0.00098)	(0.00023)	(0.0011)	(0.00076)
3-4 Month Lead	-0.00078	0.00014	-0.00072	0.0018**
	(0.00098)	(0.00023)	(0.0011)	(0.00075)
5-6 Month Lead	-0.00028	0.00045*	0.00092	-0.0019**
	(0.00097)	(0.00024)	(0.0011)	(0.00074)
7-8 Month Lead	0.00019	-0.000057	0.00070	-0.00096
	(0.00096)	(0.00022)	(0.0011)	(0.00071)
9-10 Month Lead	0.00063	-0.000050	0.00022	-0.00053
	(0.00092)	(0.00022)	(0.0011)	(0.00075)
11-12 Month Lead	0.0015*	0.00018	0.0013	-0.0027***
	(0.00088)	(0.00021)	(0.0011)	(0.00072)
Joint F-test on Leads	1.04	1.35	0.67	6.77
P-value of Joint F-test	0.40	0.23	0.67	0.00
Observations	263,563	263,563	263,563	263,563
R-squared	0.150	0.004	0.122	0.446
Number of Zip Codes	25,541	25,541	25,541	25,541

Clustered standard errors in parentheses (at zip code level)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
1) Regressions include month-year fixed effects, zip code fixed effects, as well as controls for age at listing, PRA, previous transplant status, blood type, gender, race, education.
2) Leads and lags are two-month averages.

Table 8: Leads and Lags of *Activity*, Quality

VARIABLES	Graft Survival >1 Year	Graft Survival >2 Years	HLA Mismatches	Registration Duration (Days)
11-12 Month Lag	-0.0010	-0.00018	-0.0031	-0.69
	(0.00096)	(0.0014)	(0.0048)	(2.18)
9-10 Month Lag	0.00046	0.0016	0.0058	3.74*
	(0.00087)	(0.0012)	(0.0048)	(2.23)
7-8 Month Lag	0.00018	0.0011	-0.0030	-6.19***
	(0.00089)	(0.0012)	(0.0048)	(2.05)
5-6 Month lag	0.0010	-0.00082	-0.00040	-3.15
	(0.00089)	(0.0013)	(0.0049)	(2.13)
3-4 Month Lag	-0.00078	0.00095	-0.0074	-0.26
	(0.00084)	(0.0012)	(0.0048)	(2.11)
1-2 Month Lag	-0.00031	-0.0013	0.000064	-3.26
	(0.00085)	(0.0013)	(0.0047)	(2.06)
Total Exchanges Nearby	0.0015***	0.0016*	0.00080	-1.86
(Excluding Own if Relevant)	(0.00056)	(0.00082)	(0.0035)	(1.58)
1-2 Month Lead	0.00011	0.00036	0.0092**	-0.89
	(0.00077)	(0.0011)	(0.0046)	(2.04)
3-4 Month Lead	-0.00033	-0.00011	0.0048	0.15
	(0.00078)	(0.0011)	(0.0046)	(1.93)
5-6 Month Lead	0.00058	-0.00037	-0.0027	-1.78
	(0.00076)	(0.0011)	(0.0046)	(1.93)
7-8 Month Lead	-0.00054	-0.00090	-0.000080	2.69
	(0.00074)	(0.0010)	(0.0044)	(1.98)
9-10 Month Lead	0.00027	0.00021	-0.00035	-0.056
	(0.00075)	(0.00098)	(0.0044)	(1.89)
11-12 Month Lead	-0.00019	-0.00084	0.00011	2.28
	(0.00069)	(0.00092)	(0.0042)	(1.85)
Joint F-test on Leads	0.19	0.35	1.14	0.83
P-value of Joint F-test	0.98	0.91	0.34	0.55
Observations	191,639	175,246	206,886	208,105
R-squared	0.009	0.012	0.062	0.136
Number of Zip Codes	23,746	23,195	24,223	24,249

Clustered standard errors in parentheses (at zip code level)
*** p<0.01, ** p<0.05, * p<0.1
1) Regressions include month-year fixed effects, zip code fixed effects, as well as controls for age at listing, PRA, previous transplant status, blood type, gender, ethnicity, education.
2) The non-death-censored graft survival variables also assume transplant survival for those whose last known status is alive with a functioning kidney transplant.
3) One-year graft survival excludes 2013-14 data, two years excludes 2012-14.
4) Leads and lags are two-month averages.

Table 9: Tests of Endogenous Patient Relocation

VARIABLES	Moved (Binary)	Moved (Binary)	Only Movers			
			Exchange	Direct Living	Anonymous	Deceased
Total Exchanges Near Current Zip at Time of TX	-0.00099 (0.00061) [0.14]					
Total Exchanges Near Original Zip at Time of TX		-0.00011 (0.00065) [0.14]				
Activity Differential Between New and Old Residential Zip			-0.00012 (0.0024) [0.02]	0.0035 (0.0040) [0.22]	-0.00030 (0.0011) [0.0081]	-0.0031 (0.0046) [0.75]
Observations	170,300	170,300	23,627	23,627	23,627	23,627
R-squared	0.023	0.023	0.031	0.102	0.014	0.102
Number of Zip Codes	22,676	22,676	10,004	10,004	10,004	10,004

Clustered standard errors in parentheses (at zip code level)
*** p<0.01, ** p<0.05, * p<0.1
Means of dependent variables in brackets.
1) Regressions include month-year fixed effects, zip code fixed effects, as well as controls for age at listing, PRA, previous transplant status, blood type, gender, race, education.

Table 10: Measuring Substitution, Robustness Checks

| VARIABLES Mean of Y	Exchange (First Stage) [0.014]	Direct Living [0.28]	Anonymous [0.0052]	Deceased [0.49]	Died on WL [0.21]	Too Sick or Refused Tx [see below]
Original	0.0056*** (0.00034)	-0.50*** (0.11)	0.12*** (0.031)	-0.086 (0.13)	-0.54*** (0.093)	
Using One- and Two-Month Lags	0.0018*** (0.00030)	-0.68*** (0.23)	0.21*** (0.061)	0.48 (0.30)	-1.02*** (0.21)	
(Two Month Lag)	0.0015*** (0.00031)					
Six-month Lagged Activity Total	0.00077*** (0.000071)	-0.61*** (0.21)	0.28*** (0.064)	0.59** (0.26)	-1.26*** (0.20)	
Aggregating to Zip-Month	0.0068*** (0.00040)	-0.52*** (0.11)	0.13*** (0.029)	-0.039 (0.13)	-0.50*** (0.099)	
Using 30 Mile Radius	0.0054*** (0.00042)	-0.40*** (0.13)	0.20*** (0.043)	-0.23 (0.16)	-0.57*** (0.12)	
Using 75 Mile Radius	0.0051*** (0.00029)	-0.35*** (0.10)	0.11*** (0.027)	-0.13 (0.12)	-0.63*** (0.092)	
Including Exits due to Refusal or Too sick Mean of DV	0.0049*** (0.00031) [0.013]	-0.53*** (0.11) [0.26]	0.13*** (0.031) [0.005]	-0.12 (0.13) [0.45]	-0.62*** (0.11) [0.19]	0.14* (0.081) [0.08]

Clustered standard errors in parentheses (at zip code level); *** $p<0.01$, ** $p<0.05$, * $p<0.1$
1) Regressions include month-year fixed effects, zip code fixed effects, and controls for age at listing, previous transplant status, PRA, blood type, gender, ethnicity, education.

Table 11: Quality Measures, Robustness Checks

VARIABLES Mean of Y	Graft Survival >1 year [0.93]	Graft Survival >2 years [0.88]	HLA Mismatches [3.64]	Registration Duration (Days) [597]
Original	0.20***	0.19*	0.40	-592***
	(0.066)	(0.097)	(0.38)	(170)
Using One- and Two- Month Lags	0.11 (0.13)	-0.11 (0.23)	0.52 (0.76)	-1,350*** (350)
Total Activity in the Past 6 months	0.10 (0.11)	0.050 (0.18)	0.25 (0.68)	-1,470*** (317)
Using 30 Mile Radius	0.21***	0.23**	0.47	-425**
	(0.075)	(0.11)	(0.46)	(203)
Using 75 Mile Radius	0.15**	0.12	0.51	-505***
	(0.065)	(0.10)	(0.36)	(157)

Clustered standard errors in parentheses (at zip code level); *** p<0.01, ** p<0.05, * p<0.1
1) Regressions include month-year fixed effects, zip code fixed effects, as well as controls for age at listing, PRA, previous transplant status, blood type, gender, ethnicity, education.
2) The non-death-censored graft survival variables also assume transplant survival for those whose last known status is alive with a functioning kidney transplant.
3) One-year graft survival excludes 2013-14 data, two years excludes 2012-14.

Figure 1: Kidney Transplants/Waiting List Size, Per 1,000,000 U.S. Residents

Source: Public OPTN data as of 5/6/2015, http://optn.transplant.hrsa.gov
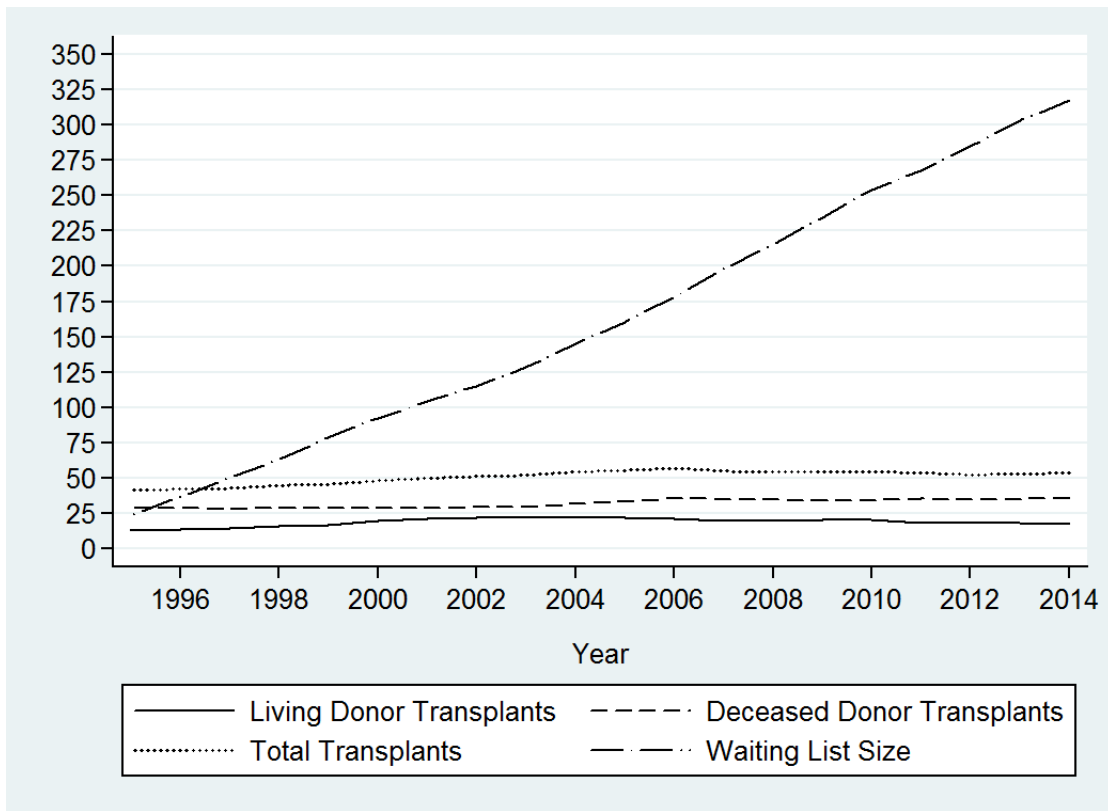
Figure 2: Transplants by Donor Type, Per 1,000,000 U.S. Population

Source: Public OPTN data as of 5/6/2015, http://optn.transplant.hrsa.gov
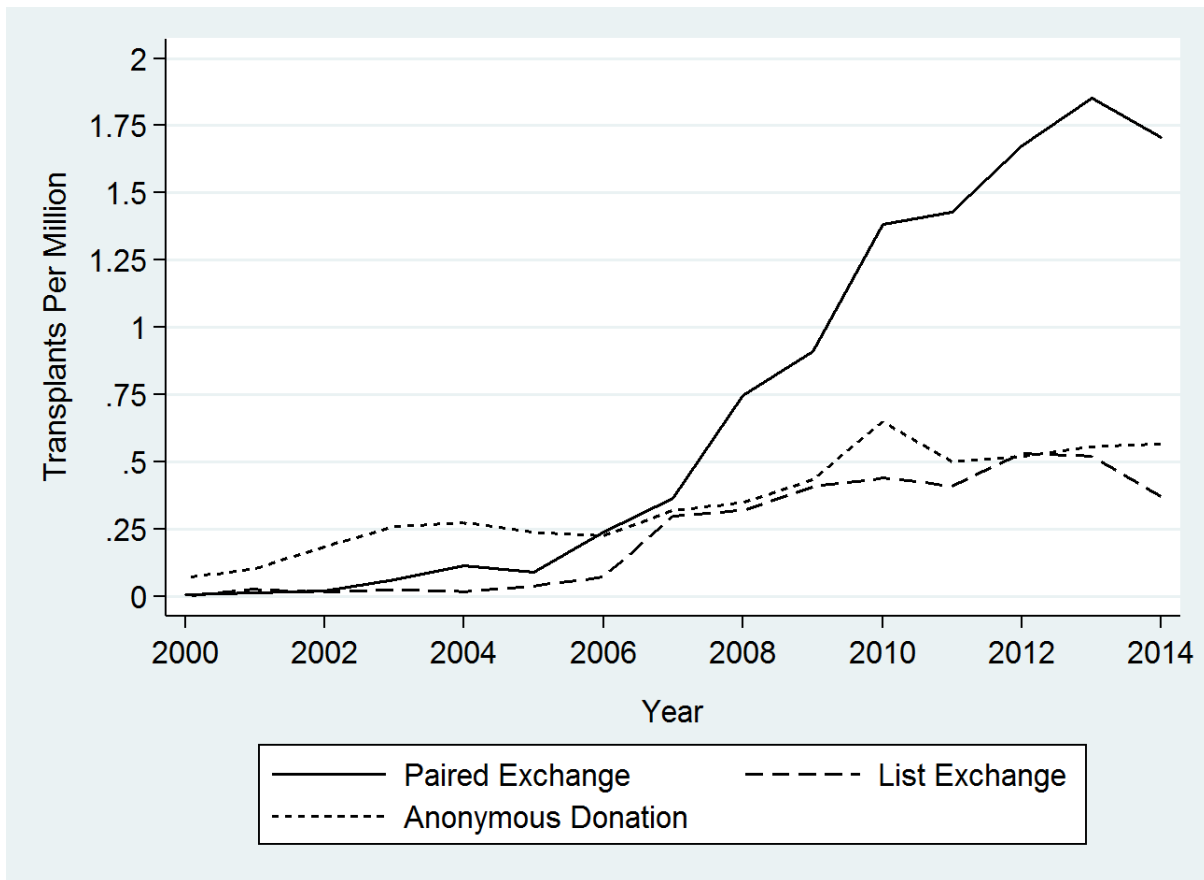
Figure 3: Transplants by Donor Type, Per 1,000,000 U.S. Population

Source: Public OPTN data as of 5/6/2015, http://optn.transplant.hrsa.gov
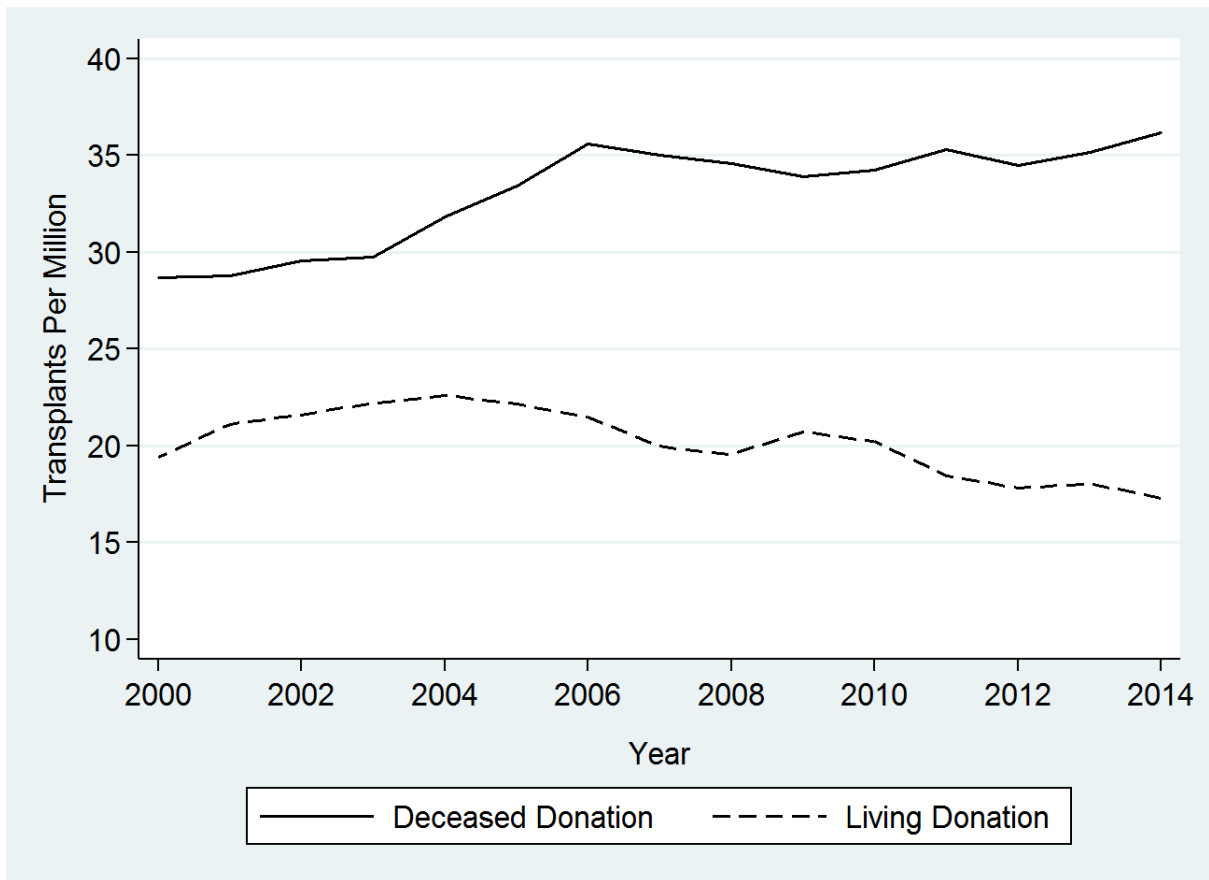
Figure 4: Transplants by Donor Type, Per 1,000,000 U.S. Population

Source: Public OPTN data as of 5/6/2015, http://optn.transplant.hrsa.gov
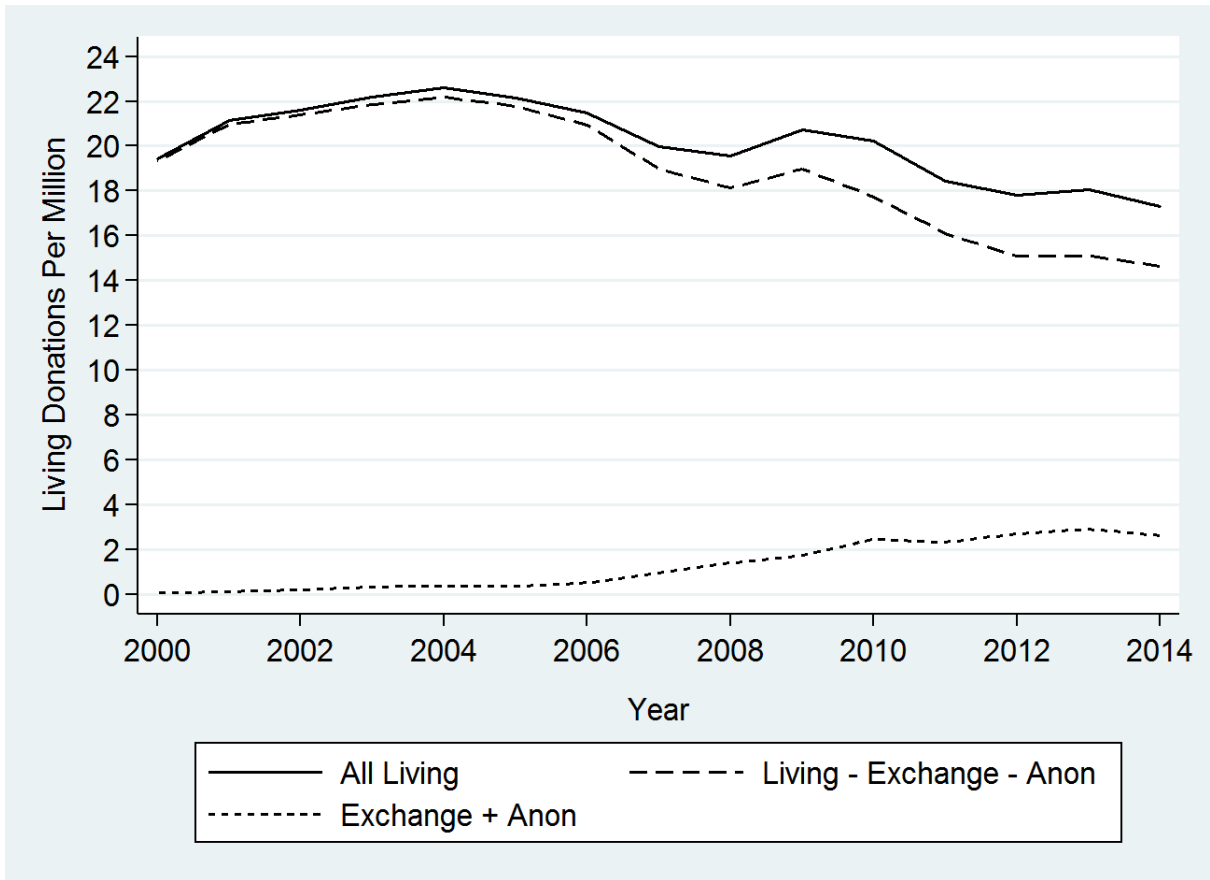
Figure 5: Two-way and Three-way Exchange, and Donor Chain Diagrams
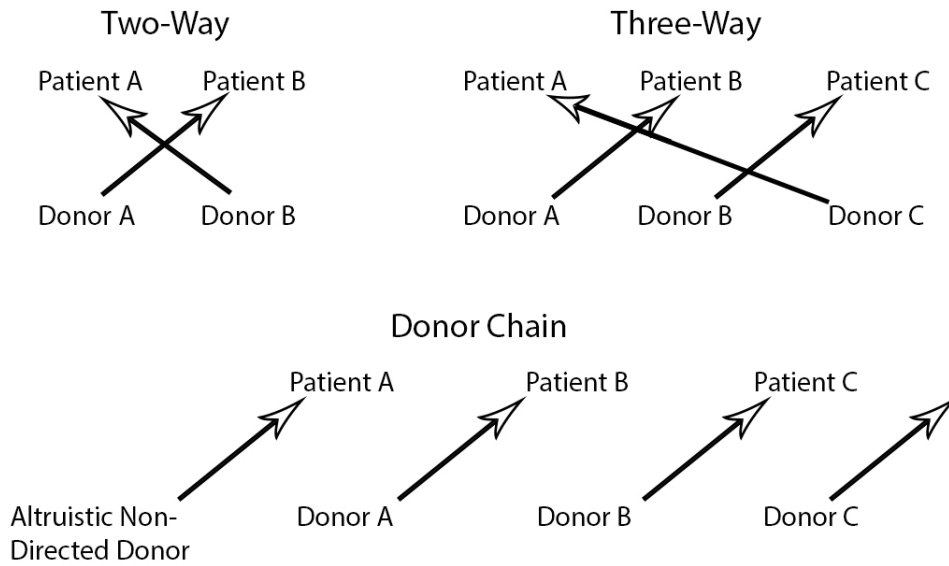
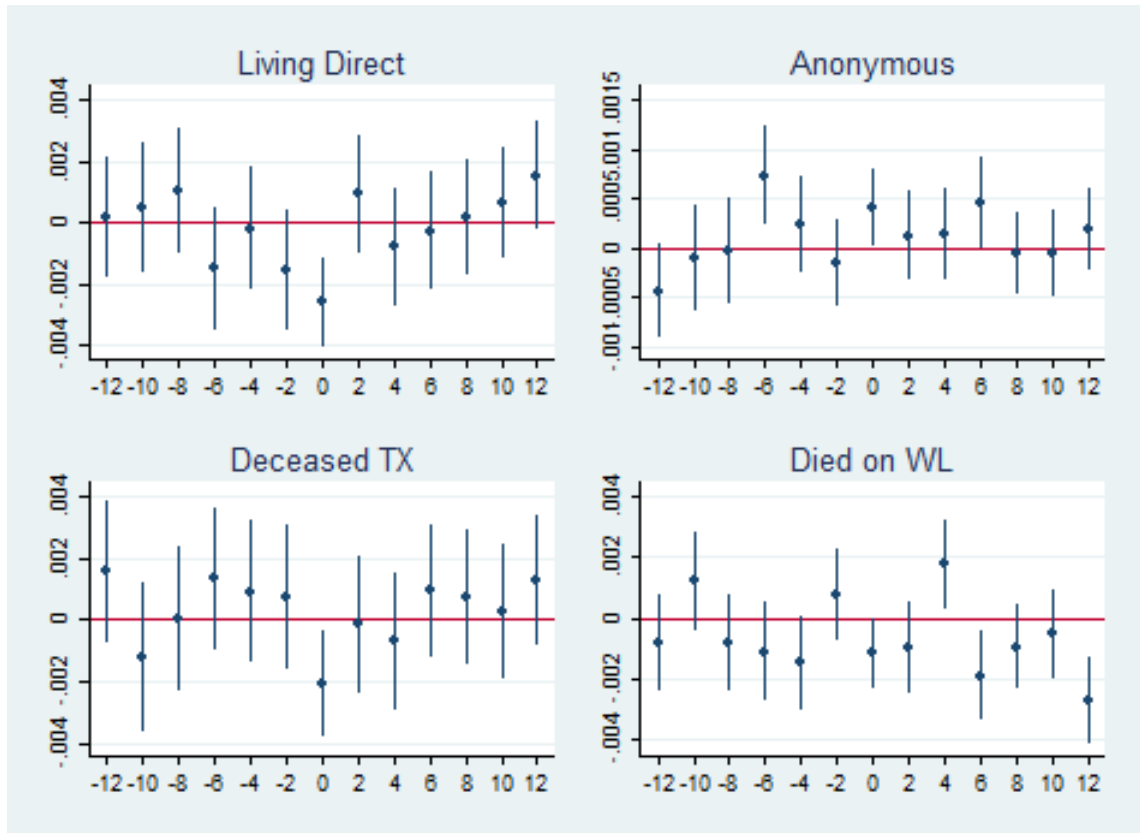Figure 6: Centers Performing At Least One Paired or List Exchange, or Both
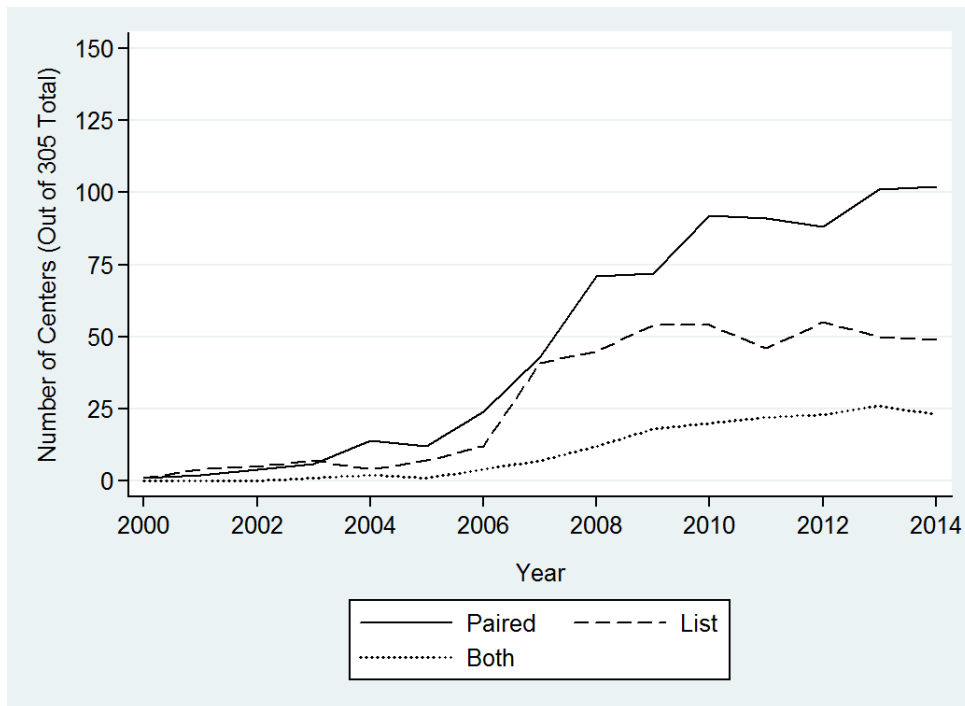
Source: OPTN STAR Data as of 12/31/2014.

Figure 7: Number of Exchanges Within 50 Miles, Excluding Own
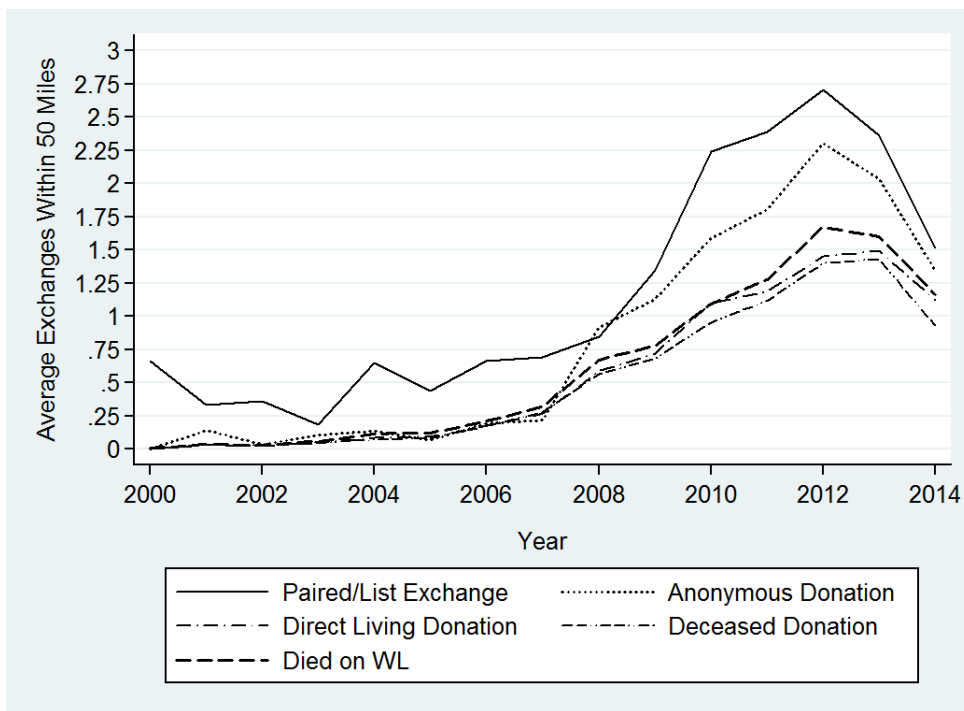
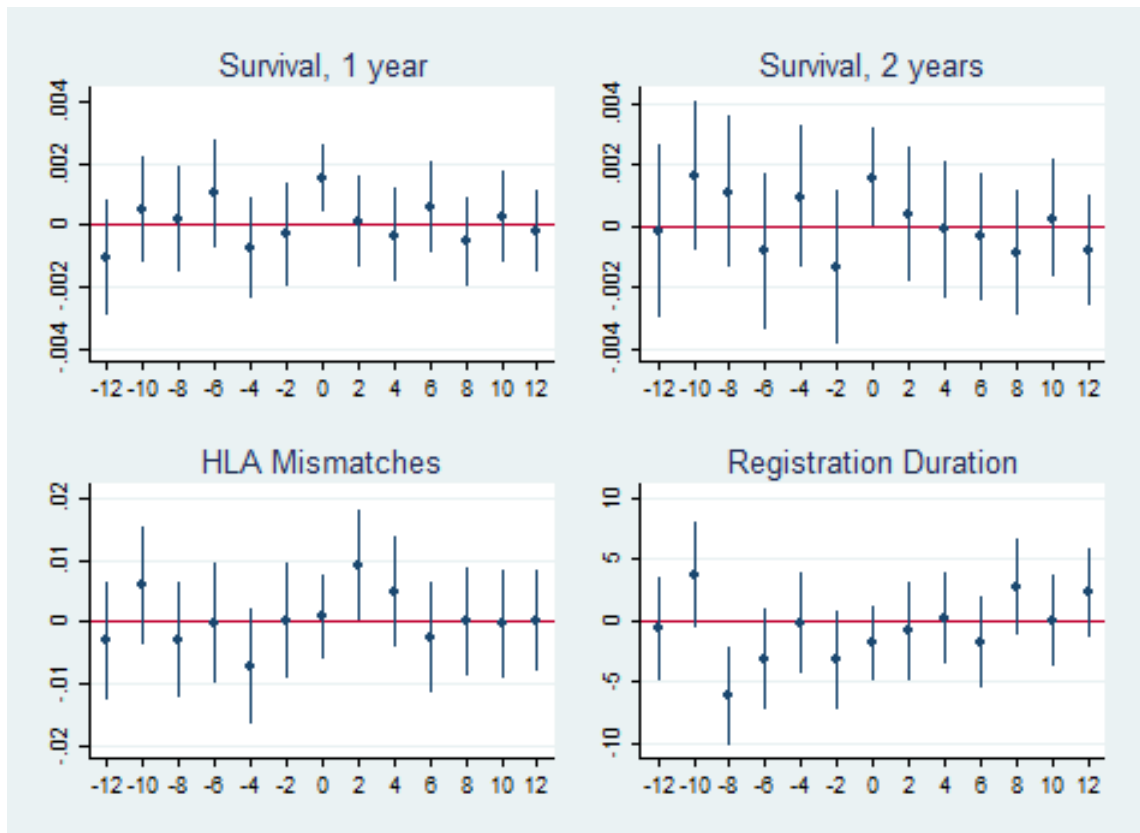Source: OPTN STAR Data as of 12/31/2014.

Figure 8: Leads and Lags of *Activity*, Registration Outcomes

Estimates from Table 7. Joint F-test on Leads: 1.04 (Direct Living),
1.35 (Anonymous), 0.67 (Deceased), 6.77*** (Died on WL)

Figure 9: Leads and Lags of *Activity*, Quality Outcomes

Estimates from Table 8. Joint F-test on Leads: 0.19 (1-year Survival), 0.35 (2-year Survival), 1.14 (HLA Mismatches), 0.83 (Registration Duration)